The Essays on Election Fraud in Authoritarian Regimes

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Political Science)
in The University of Michigan
2017

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To Mom

ACKNOWLEDGEMENTS

During my years at Michigan, I've been surrounded by many great and exceptionally smart people from whom I've learned a lot. I am extremely grateful for all of the support and advice that I've received while working on this dissertation in both the Department of Political Science and the Center for Political Studies at Michigan. First and foremost, I would like to thank two people who helped me to develop as a scholar. Walter Mebane, my committee chair, supervisor and mentor. I feel incredibly fortunate to have had him around from the start of my first year in the program: Walter helped me to shape my research agenda and sharpen my dissertation ideas, provided solid support during my long PhD journey. His brilliance and optimism have always inspired and energized me. I'm also incredibly grateful to Bill Zimmerman, who helped me to discover Michigan, and provided his mentorship throughout my graduate career. I'm really lucky to have had Bill by my side, as he was always ready to encourage me, support me, and share his exciting stories about the USSR and Russia, and his experiences with Soviets and Russians. He pushed me hard to graduate, but I delayed until the Michigan's Bicentennial!

I want to thank my committee members Ken Kollman and Allen Hicken for being supportive and conscious during my hard times. Together with Walter, Ken, Allen – we managed to develop and put to life the Election Forensics Toolkit, which I'm really proud of, and which exposed me to an enjoyable teamwork experience. I'm also thankful to Jenna Bednar and Michael Traugott for joining the committee, and helping me to discover ideas which laid the foundation of my present research.

In addition to my committee members, on different stages in the program I have received invaluable advice and important support from many people along the way. Many, many thanks go to Elvira Balandina, Julia Baskakova, Gavril Bilev, Bill Clark, Fred Conrad, Natalia Demina, Sasha de Vogel, Ruben Enikolopov, Natalia Forrat, Vladimir Gel'man, Grigorii Golosov, Alexey Grazhdankin, Olga Gurova, Valery Fedorov, Rob Franzese, Henry Hale, Huzefa Khalil, Polina Kozyreva, Jim Lepkowski, Arkady Lubarev, Ethan Miles, Jim Morrow, Mitch&Sue Mitchell, Donna Parmelee, Veronika Pasynkova, Maria Petrova, Eduard Ponarin, Alla Samoletova, Sergey Shpilkin, Konstantin Sonin, Igor Zadorin, Kirill Zotov. I'm also thankful to Grover Barnard, who is no longer with us – Grover was the person who originally sparked my interest in quantitative methodology, and he helped me take my first steps in statistical analysis many years ago.

I want to thank participants of the CPS Interdisciplinary Workshop on Politics and Policy, the MPSA panels, and the APSA panels, where I presented initial drafts and received invaluable feedback. Additionally, I want to extend my sincere gratitude to the Center for Political Studies. For many years, it has become my true academic home, thanks to Barbara Opal, David Howell, Lauren Guggenheim and many others.

I am particularly grateful for the organizations whose financial support was crucial to my research success: the Fulbright Scholar Program in Russia, the Carnegie Corporation of New York, the Weiser Center for Emerging Democracies, the Department of Political Science at Michigan, and the Rackham Graduate School. My fieldwork in Russia in 2012 could've been impossible without assistance of the New Economic School in Moscow and my *alma mater* the European University at St.Petersburg.

I also want to thank my sister Gelya and nephew Norman whom I was very lucky to meet several years ago, and who have been supportive of my American endeavors since then. I also want to thank the very person, whose name I'll omit here, who inspired me long ago while we were both in St.Petersburg, to return to the US, challenge myself and do the best of my abilities. And finally, I owe my deepest gratitude to my Mom who was always there for me no matter what — thank you, Mom!

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ABSTRACT

The Essays on Election Fraud in Authoritarian Regimes

by

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Chair: Walter R. Mebane, Jr.

My dissertation is focused on the exploration of methodological and theoretical aspects of the statistical detection of election fraud, as well as the development and testing of theories designed to facilitate our understanding of election fraud and its origin in an authoritarian regimes. It revolves around three major research questions: "Can the finite mixture model's estimates be validated against alternative data sources used to identify electoral anomalies and determine the magnitude of election frauds?", "How do specific patterns in electoral data related to election fraud enable autocrats to identify and reward their most loyal subnational agents?", and "What is the general mechanism behind a close match between polls and rigged election results in autocracies?" It fills this analytic gap by offering two formal models to explain the mechanisms by which autocrats, local agents, and survey organizations act in the context of the informational uncertainties generated by authoritarian regimes. The formal models help to clarify my core assumptions, build internally consistent theories, and derive valid hypotheses.

My first chapter explores whether election fraud precinct-level estimates obtained from a finite mixture likelihood model, recently developed by Mebane (2016), can be validated against alternative, more intuitive measures of election fraud. In this chapter

the estimated precinct-level probabilities from the parametric model of election fraud are compared against measures based on election observation, different voting modes as well as several forensics indicators. This study also tests how well the new measure matches our theoretical expectations regarding geographic distribution of election fraud. Here I utilize propensity score matching, correlation analysis, and election forensics cluster detection methods. My entire analysis is built on the data from the 2011-2012 Russian federal elections.

My second chapter focuses on the exploration of how political loyalty of subnational agents can be associated with election fraud. It introduces a novel theoretical approach towards understanding election fraud under autocracies by suggesting a signaling model of election fraud and testing its basic implications on unique datasets from Russian and cross-national settings. According to the theory, the heads of subnational units can send their signals about loyalty to the leader by means of fraudulently augmented turnout or incumbent's vote percentages. In return, the local agents are rewarded by the leader with the larger amounts of postelectoral fiscal transfers. Basic implications from the formal model are supported by empirical data analysis of the Russian and cross-national data.

My third chapter explores whether election fraud can be conducive to the enhancement of electoral credibility in electoral autocracies. It provides an innovative perspective on the mechanism by which the autocrats in electoral autocracies strategically benefit from preference falsification, which boosts their own electoral ratings and encourages perpetration of election fraud. This chapter extends Kuran (1991)'s model by adding to the model the concept of election fraud. Theoretical implications of the model are tested on the original survey data collected by the author in Spring 2012 during the Russian presidential campaign, as well as original cross-national data including 59 countries. My theory is supported by empirical findings.

A practical consequence that follows from this dissertation is that the theories and methods presented here can enhance our understanding of election fraud in autocracies and contribute to the development of the empirical applications, such as Election Forensics Toolkit.

CHAPTER I

Introduction

On 18 May, 2012, after walking in the tangled labyrinth of unostentatious state buildings of Lubyanka district in Moscow, I found myself in front of the green façade of the Central Election Commission, with its vigilant federal security officers guarding the entrance. The atmosphere in the country was rather gloomy: a few months earlier, Russia hosted its parliamentary and presidential elections, which marked the return of Putin to power and spawned massive protests in Moscow and St. Petersburg amidst numerous allegations of fraud. That year, the Central Election Commission had been the subject of public criticism regarding its involvement in electoral malfeasance. In a few moments a friend whom I had known for many years stepped outside of the building and cheerfully greeted me."Welcome to the residence of evil," he grimly joked, and added "Perhaps, you should be very excited about what you are about to see, since you studied all this for years". I agreed. The building's interior clearly received a very expensive renovation, with many translucent materials used ostensibly to create an impression of transparency and wealth. After taking a glass elevator to one of the upper floors, we entered a small room where four of us engage in several hours of conversation over tea, touching on a wide range of topics from opposition rallies and leaders to elections and election forensics methodology. My interlocutors, who occupied top positions within the Commission's system, appeared dreary and unemotional. However, they all were genuinely interested in meeting someone who does election forensics analysis and sought to learn more about the tools used to detect electoral *anomalies. In fact, one of the papers which we published with Walter Mebane in Russian a few years ago provided them with some helpful guidance (Mebane & Kalinin 2009b). That paper specifically focused on the application of Benford's Law–which uses theoretical mean of the second digit 4.187 as an expectation for clean elections, within certain bounds of uncertainty–in detecting election anomalies in Russia's 2003-2004 and 2007-2008 elections.*

The meeting soon ended and could've easily been forgotten by all parties. But five years later it turned out that the results of the 2016 parliamentary elections computed for 96,869 precincts matched the theoretical mean of the second digit by precisely four significant digits, 4.187, which is an extremely rare event even in a democratic setting. This story appeared in the Washington Post's Monkey Cage blog (Kalinin & Mebane 2017a), suggesting that the Russian government might have pretty good skills at faking vote data, and then made waves in the Russian media. Perhaps this observation could've occurred by chance alone; perhaps the Russian elections are so well-managed by the Center that such close matches are possible – we simply do not know. The Russian government denies any allegations of electoral violations. However, if the latter is correct, then that meeting could've been regarded as a unique scientific experiment proving that modern autocrats take election forensics seriously and can use technology to out-trick modern methods.

This introductory episode shows the importance of electoral manipulation in authoritarian regimes and election forensics methodology to uncover it. In fact, the durability of authoritarian regimes to a large extent originates from their capacity to effectively undermine electoral challenges from the opposition via media, state institutions or elections. In this sense, the quality of elections has been the subject of concern for a long time with autocrats very often resorting to electoral manipulations aimed to minimize uncertainty over favorable electoral outcomes and discourage political opposition by signaling their electoral or "manipulative" strength (Magaloni 2006; Simpser 2013). Moreover, elections solidify the legitimacy of the autocrat among the general public (Geddes 2006; Magaloni 2006). Elections can provide lots of information that allows assessment of the strength of the potential opposition in society, even if the signal is somewhat noisy due to attempts at manipulation and fraud (Gandhi 2008, 167).

Election fraud is an inherently opaque phenomenon. Its definition therefore helps to provide conceptual clarity and set necessary methodological benchmarks. Despite the variation across its competing definitions, election fraud can be defined from both procedural and coercive perspectives. The first approach views election fraud as "a conduct intended to corrupt the process by which ballots are obtained, marked, or tabulated; the process by which election results are canvassed and certified" (Donsanto 2008). Here election fraud implies clandestine efforts on the part of the perpetrators to shape election results in a desirable direction (Lehoucq 2003). This definition makes sense in well-established democracies, but is not applicable to autocracies which lack solid democratic institutions and are prone to violence exerted upon political opposition (Cavdar 2008). In my dissertation, I will resort to the second approach using Walter Mebane's definition of election fraud, which defines election fraud as a "consequence of a situation in which all votes are cast in a way that reflects some single person's intention," in this sense, "voters who act in line with threats or bribes are being coerced, and simple ballot box stuffing also counts as coercion." (Mebane 2012)

While its hidden origin complicates exploration of election fraud, fraud can leave specific footprints in the electoral data, which election forensics researchers intend to expose. From a practical standpoint, this daunting task is challenging due to the data availability issues related to the lack of fine-grained data and suitable covariates for building complex explanatory models of election fraud. Unfortunately, the variability of political systems, electoral systems, cultural and social norms have complicated this problem even further, making any election forensics research quite a daunting task to implement.

Election forensics adds distinctive value to current efforts to promote the integrity of elections around the world by developing forensic tools and techniques designed to detect the presence of election fraud and to estimate its magnitude based on the reported results of elections. By utilizing electoral data, election forensics seeks to provide statistical evidence, which could refute or support various sorts of accusations related to the presence of election fraud. Over the years the availability of election forensics tools has significantly expanded starting from various digit-based tests, such as the first digits of aggregate vote totals (Cantu & Saiegh 2011), second significant digits (Mebane 2011; Pericchi & Torres 2011), the last digits in vote counts (Beber & Scacco 2008) or last digits in percentages (Kalinin & Mebane 2013), to various distribution-based methods proposed by Myagkov, Ordeshook, and Shaikin (2009); Shpilkin (2011) and regression analysis (Sobyanin & Sukhovolsky 1995). Most recently, however, Klimek, Yegorov, Hanel, and Thurner (2012) proposed the positive empirical model of election frauds, suggesting that there is a winning party or candidate, i.e. with most votes, benefiting from the votes transferred from other parties/candidates and nonvoters. Mebane (2016), based on Klimek et al. (2012), further develops the model by utilizing a finite mixture likelihood model which estimates three distinct components measured at the precinct level: probabilities of incremental fraud, extreme fraud and no fraud. The new approach to election forensics enables scholars to parametrically estimate the precinct-level frauds probabilities obtained for an entire election by using sophisticated statistical algorithms, and provides a promising alternative to descriptive and oftentimes debatable assumptions (Deckert, Myagkov, & Ordeshook 2011; Mebane 2014). Based on Klimek's model, it's possible to derive two fraud parameters: *incremental fraud*, measuring the transfer of moderate votes proportions and *extreme fraud*, showing the extreme cases of votes transfer of votes inside the precinct. The development of election forensics methodology has led to creation of the "Election Forensics Toolkit" website sponsored by the USAID and developed by Walter Mebane and Kirill Kalinin. The project has been specifically designed to make election forensics accessible for the use of policymakers, practitioners, and scholars. Most of the empirical analysis presented in this research has been conducted through the Toolkit.

My dissertation is focused on the exploration of methodological and theoretical aspects of the statistical detection of election fraud, as well as the development and testing of theories designed to facilitate our understanding of election fraud and its origin in authoritarian regimes. My work revolves around three major research questions: "Can the finite mixture model's estimates be validated against alternative data sources used to identify electoral anomalies and determine the magnitude of election frauds?", "How do specific patterns in electoral data related to election fraud enable autocrats to identify and reward their most loyal subnational agents?", and "What is the general mechanism behind a close match between polls and rigged election results in autocracies?" My work fills this analytic gap by offering two formal models to explain the mechanisms by which autocrats, local agents and survey organizations act in the context of the informational uncertainties generated by authoritarian regimes. I also provide empirical tests of these theories, derive the measures of electoral anomalies using the Election Forensics Toolkit, and discuss the best election forensics techniques.

My first chapter focuses on validation of the finite mixture model – the most advanced up-to-date method of election forensics analysis, which is currently under development and therefore requires a series of validity checks. Based on the Russian electoral data, this chapter attempts to find answers to the set of the following questions: Does the new finite mixture estimator more or less correctly predict the results from the available field experiments? How well the new measure matches our theoretical expectations regarding geographic distribution of election fraud? How well does the distribution of geographical clusters of the finite mixture estimates correlate with the geographical clusters of different election forensics estimates? To answer these questions I utilize a broad range of available techniques: propensity score matching, correlation analysis, and election forensics cluster detection methods. My entire analysis is built on the data from the Russian elections of 2000s. In fact, as abundance of evidence illustrate, in the 2000s the growing authoritarian tendencies in Russian political system has exacerbated the problem of blatant election fraud and various electoral manipulations even further, making it an interesting subject of research by many scholars. Availability of precinct-level electoral data and alternative data sources, such as the data on election observation and installation of electronic voting machines, makes the Russian case valuable for the methodological validation of a new measure. In this chapter I specifically focus of 2011 parliamentary and 2012 presidential elections.

In my second chapter I focus on the exploration of how the political loyalty of subnational agents can be associated with election fraud. Elections can elicit information about election fraud itself: specific patterns in electoral data can persist conditional on the strategies of officials and their success in signaling the loyalty to the leader. This information is especially valuable to the autocrat, who can use the electoral data to get a snapshot of the loyalty status of the local agents, and decide on each agent's success in mobilizing his regional "political machine" to provide necessary electoral support to the leader (Gel'man 2009). While the previous research has shown that, in Russia and elsewhere, fraud can often be readily detected (Mebane & Kalinin 2009b; Myagkov & Ordeshook 2008; Myagkov, Ordeshook, & Shaikin 2008; Myagkov et al. 2009), it has rarely focused on the mechanisms by which election fraud can be conducted nationally. My theory describes whether local agents engage in a signaling strategy, wherein election fraud signals loyalty to the leader, who distributes post-election rewards and punishments based on electoral results and turnout. This approach allows us to explain the prevalence of anomalous data patterns in turnout and voting percentage data, specifically the frequency with which a 0 or 5 appears as the last digit in a percentage. The Russian case exemplifies this phenomenon quite well: while in the mid-1990s Russian governors used strategies of bargaining, in which powerful regions provided the leader with favorable electoral outcomes in exchange for political, institutional and financial resources (Treisman 1997a, 1997b), political recentralization in the 2000s has led to revision of bargaining agreements and the imposition of electoral signaling. In the Russian case this strategy is employed by regional governors to signal their loyalty to the leader by means of fraudulently augmented electoral results and to get certain rewards in exchange, such as political survival or postelectoral transfers. The expansion of the "signaling game" to the cross-national realm is possible through the classification of different emergent equilibria. Specifically, the presence of rigged elections and associated numerical anomalies either in democracies or autocracies can be explained by a combination of various institutional factors such as regime type (authoritarian or democratic), system of government (federal or unitary), and form of government (presidential vs. parliamentary). In sum, all these factors preset a specific level of loyalty of local agents *via-a-vis* the leader, leading to the described strategic behavior expressed in signaling strategies.

In my third chapter I explore if election fraud can be conducive to the enhancement of electoral credibility in electoral autocracies. It provides an innovative perspective on the mechanism by which the autocrats in electoral autocracies strategically benefit from preference falsification, which boosts their own electoral ratings and encourages perpetration of election fraud. My theory suggests that election fraud serves as a by-product of pre-election forecasts that are contaminated with the preference falsification, creating leeway for numerous electoral violations, including election fraud. Within this framework, election fraud is designed to mask the discrepancy between incumbent's inflated electoral support and genuine electoral preferences. Ideally, the presence of the observed close match between polling forecasts and election results enables the autocrat not only to claim his electoral legitimacy validated by pre-election polling, but also to reveal the weaknesses of political opposition unable to enjoy such extensive public support. If, however, any of such mismatches occur these goals are severely undermined and electoral credibility is jeopardized. Theoretically, this chapter builds on Timur Kuran's work on preference falsification, by adjusting his basic model to the topic of election fraud (Kuran 1987, 1991). Within this framework, election fraud is designed to mask the discrepancy between endogenously determined public and private pre-electoral preferences, and guarantee the autocrat a stable equilibrium. The contribution of this chapter to the existing literature is threefold. First, this chapter extends Kuran's model by adding to the model the concept of election fraud, and thus offers a mechanism by which an incumbent insures his most desirable electoral outcome. Second, this chapter tests the theoretical implications of the model by utilizing original survey data collected by the author in Spring 2012 during the Russian presidential campaign. In contrast to conventional election forensics research, which does not consider the dimension of public opinion surveys, this research demonstrates strong empirical findings with respect to the effect of preference falsification on the level of election fraud in electoral autocracy. Third, I compare the reliability of two types of election fraud indicators: two digit-based tests and the model-based measure of election fraud. In order to extend my findings beyond the Russian case, I also apply a statistical analysis of 59 countries with the inclusion of both electoral autocracies and democracies.

The conclusion summarizes some of the main points and discusses the prospects of future research in election forensics methodology.

CHAPTER II

Validation of the Finite Mixture Model Using Quasi-Experimental Data and Geography

2.1 Introduction

Election forensics adds distinctive value to current efforts to promote the integrity of elections around the world by developing forensic tools and techniques designed to detect the presence of election fraud and to estimate its magnitude based on the reported results of elections. By utilizing electoral data, election forensics seeks to provide statistical evidence, which could refute or support various sorts of accusations related to the presence of election fraud. Since election fraud is increasingly difficult to measure, validation studies aimed to test whether the conceptual ideas of election fraud are plausibly measured by election forensics methods, become the integral part of election forensics research. In this sense, any auxiliary data containing information on electoral anomalies and violations, collected through some objective process can serve as a validation check against election forensics measures.

A new breakthrough in election forensics due to the emergence of the positive empirical model of election frauds (Mebane 2016) opens new valuable opportunities for scholars and practitioners interested in exploring election frauds in multiple electoral settings. It also raises the issue of validity of a new estimator. The Russian case clearly raises several valuable opportunities for validation of this new methodology. By employing the electoral data from the Russian 2011 and 2012 presidential elections both of which are notoriously fraudulent (Enikolopov, Korovkin, Petrova, Sonin, & Zakharov 2013; Kalinin & Shpilkin 2012; Klimek et al. 2012; Kobak, Shpilkin, & Pshenichnikov 2012) and the auxiliary data from field experiments and alternative data sources, it becomes feasible to assess the validity of a new forensics measure.

The newly developed election forensics estimator belongs to a variety of election forensics methods. Over the years the availability of such methods has significantly expanded starting from various digit-based tests, such as the first digits of aggregate vote totals (Cantu & Saiegh 2011), second significant digits (Mebane 2011; Pericchi & Torres 2011), the last digits in vote counts (Beber & Scacco 2008) or last digits in percentages (Kalinin & Mebane 2013), to various distribution-based methods proposed by Myagkov et al. (2009); Shpilkin (2011), regression analysis (Sobyanin & Sukhovolsky 1995) and parametric models of election fraud (Klimek et al. 2012; Mebane 2016). Each of the election forensics measures makes different implicit or explicit assumptions regarding the data generating mechanism of the "clean data" with some methods being more suitable than others depending on the electoral context and the research question.

The development of election forensics methodology has led to creation of an "Election Forensics Toolkit" website sponsored by the USAID and developed by Walter Mebane and Kirill Kalinin. The project has been specifically designed to make election forensics accessible for the use of policymakers, practitioners, and scholars.[1] Most of the empirical analysis presented here utilized the code from the Toolkit. Besides using election forensics methods with electoral data, this chapter also engages experimental data: two field experiments based on the data from election observers and the data on voting equipment

[1] Major election forensics methods, such as the derivation of the finite mixture estimates and building maps containing the results of clustering analysis, have used the *Election Forensics Toolkit*. The *Election Forensics Toolkit* is a web application, which has been technically implemented by Walter Mebane and Kirill Kalinin. The Toolkit is designed to conduct election forensics analysis using the publicly accessible website. The link to the website: http://electionforensics.ddns.net:3838/EFT_USAID/

in the precincts.

This research will focus on validation of the finite mixture model estimates for a number of reasons. First, this is the most advanced method of election forensics analysis to date, but it is currently under development and therefore requires a series of validation checks. Second, conditional on the assumption that the finite mixture model is correct, unlike all other approaches, the model provides the quantities of greatest substantive interest for researchers and practitioners, i.e. fraud probabilities of two distinctive mechanisms – incremental and extreme fraud. Third, the finite mixture estimates for the precinct-level data are provided at the lowest level of aggregation, making validation study more nuanced and precise, especially when auxiliary data at this level is available. This set of properties of the finite mixture model makes its validation study particularly appealing and promising for election forensics research.

Here I attempt to find answers to the set of the following questions: Does the new finite mixture estimator more or less correctly predict the results from the available field experiments? How well the new measure matches our theoretical expectations regarding geographic distribution of election fraud? How well does the distribution of geographical clusters of the finite mixture estimates correlate with the geographical clusters of different election forensics estimates for which the mechanism of election fraud is already known? To answer these questions I utilize a broad range of available techniques: propensity score matching, correlation analysis, and election forensics cluster detection methods.

The structure of this paper is as follows. Sections 2.2 and 2.3 describe the literature on election forensics methodology. Section 2.4 lays out the context of the Russian elections and discusses availability of the relevant Russian data. Section 2.5 describes methodological tools and formulates a set of hypotheses. Section 2.6 presents my general findings from empirical analysis based on experimental evidence, correlation analysis and clustering analysis using both precinct-level and territory-level data. In the final part, I draw conclusions on the basis of my findings and discuss the prospects of future research.

2.2 Measuring Election Fraud

The durability of authoritarian regimes to a large extent originates in their capacity to effectively undermine electoral challenges from the opposition via media, state institutions or elections. In this sense, the quality of elections has been the subject of concern for a long time, with autocrats very often resorting to electoral manipulations aimed to minimize uncertainty over favorable electoral outcomes and discourage political opposition by signaling their electoral or "manipulative" strength (Greene 2007; Magaloni 2006; Simpser 2013). Since election fraud is an inherently opaque phenomenon, its initial definition will provide conceptual clarity and set necessary methodological benchmarks for my forthcoming empirical analysis. Despite variation in its competing definitions, election fraud can be defined from two major perspectives – procedural and coercive. The first approach views election fraud as "a conduct intended to corrupt the process by which ballots are obtained, marked, or tabulated; the process by which election results are canvassed and certified" (Donsanto 2008). Here election fraud implies clandestine efforts on the part of the perpetrators to shape election results in a desired direction (Lehoucq 2003). This "procedural" definition, however, makes sense in well-established democracies with developed electoral institutions and clear organization procedures, but is hardly applicable to autocracies which lack solid democratic institutions and are prone to political violence exerted upon the opposition (Cavdar 2008). Therefore in my dissertation I will resort to the second approach using Mebane (2012)'s definition of election fraud based on Arrow (1950)'s impossibility theorem, defining it as a "consequence of a situation in which all votes are cast in a way that reflects some single person's intention," in this sense, "voters acting in line with threats or bribes are being coerced, and simple ballot box stuffing also counts as coercion."

While its hidden origin complicates exploration of election fraud, it can leave specific footprints in the electoral data, which election forensics researchers intend to expose. From a practical standpoint, the difficulty of this task is exacerbated by data availability issues related to the lack of fine-grained data and suitable covariates for building complex explanatory models of election fraud. Unfortunately, the variability of political systems, electoral systems, cultural and social norms have complicated this problem even further, making comparative election forensics research quite a daunting task to implement.

One of the most popular methodological approaches are digit tests built on comparison of empirical distributions with pre-specified theoretical distributions. Among the most popular methods are the first digits of aggregate vote totals (Cantu & Saiegh 2011), second significant digits (Mebane 2011; Pericchi & Torres 2011), the last digits in vote counts (Beber & Scacco 2008) or last digits in percentages (Kalinin & Mebane 2013). For example, while the first and second digits are expected to follow the Benford's Law (2BL) if elections are clean, last digits in vote counts or percentages are expected to follow a uniform distribution. The second digit test has been criticized as a viable election forensics method. For instance, Deckert et al. (2011) find that 2BL test is susceptible to false positives. Due to the lack of solid theory, it remains unclear how its performance is affected by election law, strategic voting patterns, the number of competing parties or candidates, and a variety of other factors. Mebane (2012); Mebane and Klaver (2015) also disavow the 2BL test and find that the second digits are sensitive to strategic, gerrymandered, and coerced votes, making it hard to disentangle strategic behavior from the effects of election fraud. Since 2BL test turned out to be invalid as a detection tool, it is no longer used in election forensics methodology.

Following Mebane (2006)'s approach, Beber and Scacco (2012) propose the last-digit test based on the idea that clean vote counts have uniformly distributed 0-9 last digits. The authors also list several conditions which need to be met for the test: a) vote counts do not cluster within a narrow range of numbers, and there is minor variation in election unit sizes, electoral support, or turnout; b) vote returns must not contain many single- and double-digit counts, i.e. the method should not be applied to the minor candidates with small vote counts or small polling stations. Once these conditions are met, any statistically significant divergence from the uniform distribution can be attributed to fraudulent electoral outcome. The last-digit approach can be extended to any electoral variables meeting the aforementioned condition. The last digit approach has been further developed by a new test of last digit of percentages, supported by the concept of signaling games. The presence of election fraud becomes a basic signaling mechanism of regional bosses' loyalty and of their ability to control their administrative resources to the Kremlin's benefit (Kalinin & Mebane 2013). If electoral signaling occurs, data manipulation is most likely to manifest with rounded percentages of electoral support, which is the easiest and most readily detected way to report basic information to superiors. An extensive analysis of the signaling concept will be provided in the next Chapter of my dissertation.

The non-digit approach utilizes different techniques. Based on normality assumption for the distribution of vote shares or turnout, certain departures from normality can be seen as electoral anomalies. Analysis of vote flows between the elections in multiple heterogeneous settings is another viable method of election forensics (Myagkov et al. 2009). Relationship between turnout and vote shares measured by correlation or regression analysis (Buzin & Lubarev 2008; Sobyanin & Sukhovolsky 1995) is proposed in a number of works. The nonparametric approach developed by Sergey Shpilkin is another viable method based on the histogram built for turnout and electoral support (Shpilkin 2011). The detailed review of election forensics methodology can be found in Hicken and Mebane (2015).

Since election fraud is increasingly difficult to measure, validation studies, testing whether the conceptual ideas of election fraud are plausibly measured, become crucial for election forensics research. Unfortunately, each of the election forensics measures makes different implicit or explicit assumptions regarding the data generating mechanism of the "clean data" with some methods being to be more suitable than others depending on the electoral context and the research question. There can't be apparent consensus regarding the validity of alternative methods being compared with one another, since, so far, no study has been conducted yet to assess which method exercises higher "election forensics" validity compared to the other methods. Such comparison of different methods is further complicated by various scales (digits, probabilities or magnitudes), levels (precinct-level or higher levels of aggregation) captured by the estimates and, presumably, different underlying vote-rigging mechanisms exposed by each of those methods.

This research will focus on the validation of the finite mixture model estimates for a number of reasons. First, this is the most advanced up-to-date method of election forensics analysis. Second, conditional on the assumption that the finite mixture model is correct, unlike all other approaches the model provides the quantities of greatest of substantive interest, i.e. fraud probabilities of two distinctive mechanisms – incremental and extreme fraud. Third, the finite mixture estimates for the precinct-level data are provided at the lowest level of aggregation making validation study more nuanced and precise. This set of features makes the validation study of the finite mixture model particularly appealing for election forensics research.

Most recently, Kalinin and Mebane (2017b) attempted to conduct a validation study based on Alexander Kireev's approach by comparing the estimates derived from the finite mixture estimator against the measures obtained with Sergey Shpilkin's approach. While Alexander Kireev's subjective evaluation of the fraud's magnitude for 2016 Duma elections is backed by his assessment of turnout's geographic anomalies, voting patterns, and invalid votes, Shpilkin's approach is based on nonparametric analysis. It uses the histogram with turnout broken into a series of intervals or bins (x-axis), within which the level of electoral support falling into each interval is calculated (y-axis) and a set of steps used to identify election anomalies. Kalinin and Mebane (2017b)'s findings indicate that the finite mixture method and Shpilkin's approach roughly agree about the ordering of which regions have many fraudulent votes and which have few, although the methods do not agree regarding the absolute magnitudes. If Kireev (2016)'s subjective assessments are viewed as appropriate for validation test, it turns out that while the finite mixture model estimates are not as good as Shpilkin (2016)'s estimates in distinguishing "average fraud" from "no fraud," they match Kireev's categories better than Shpilkin's estimates when it comes to distinguishing "strong fraud" from "average fraud." (Kalinin & Mebane 2017b).

The new validation approach put forward by my present analyses is that the validation can be reached by the use of quasi-experimental techniques well-grounded in the theory as well as previous studies exploring geographic distribution of election fraud. This paper will be specifically focused on quasi-experimental validation of the finite mixture model estimates and geographic dispersion of election forensics measures, including the final mixture estimates, both of which can turn out to be very useful in election forensics research.

Until very recently, quasi-experimental designs mostly dealing with election monitoring were utilized to tackle the set of limitations and assumptions associated with election forensics methodology. Election monitoring, by increasing emphasis on democratic rights and creation of a market of outside validation, has become an integral part of the effort to promote clean and fair elections worldwide (Bjornlund 2004). It also enables an autocrat to credibly signal his adherence to both domestic and international audiences, as well as discourages opposition from participation by exposing corrupt activities (Simpser 2006). A quasi-experimental setting using observers as the treatment enables scholars to obtain rough estimates of election fraud nationwide. For instance, research on election observation studies estimating the effects of observers on electoral outcomes in selected precincts demonstrates that the mere presence of election observers can significantly reduce election fraud (Hyde 2007, 2011; Kelley 2012; Sjoberg 2012). This, however, can also induce the monitored party to strategically adapt its behavior, by resorting to less detectable methods of vote falsification (Sjoberg 2014) or simply displacing election fraud to neighboring areas (Ichino & Schundeln 2012). For instance, Sjoberg (2014), using data from 2008 elections in Azerbaijan, argues that the increase the integrity of the electoral process is tolerated by an autocrat as long as the negative effects can be offset by other forms of manipulation.

Likewise, adoption of new voting or observation technologies at the election tend to impact the behavioral strategies of election administrators. The effects of technology on electoral behavior has been studied by Herron (2010), Sjoberg (2014), Bader (2013). Herron (2010) argues that increase of passive monitoring through installation of webcams results in lower support for pro-regime forces in Azerbaijan's electoral-type events. Another interesting avenue of research relates to installation of different voting machines. Installation of optical scan voting machine or a type of the direct-recording electronic (DRE) voting machines in the precincts, which will be discussed later, can potentially reduce traditional election fraud, such as ballot stuffing and ballot switching (Bader 2013). Also it is quite likely that the installation of new voting technologies in a limited number of precincts could have prevented the adoption of new fraudulent strategies and discouraged election perpetrators from artificial inflation of election outcomes in "conventional" ways. An active engagement of election observers in post-election audits based on a random sampling of polling stations can insure cleaner elections, deter fraud against the voting system, and enhance general public confidence in the results of elections (Estok, Nevitte, & Cowan 2002; Norden, Burstein, Hall, & Chen 2007).

Unfortunately, both observer-based and technology-based quasi-experiments oftentimes rely on poor data quality related to the failures of random treatment assignments in the majority of cases, eventually, leading to rather biased conclusions, whereas much more efficient survey designs, for instance stratified multistage sampling, are rarely utilized because of the high associated costs (Hyde 2008).

2.3 Positive Models of Election Fraud

The breakthrough in election forensics methodology happened with the development of the positive empirical model of election fraud proposed by Klimek et al. (2012). The Klimek model suggests that there is a winning party or candidate, i.e. with most votes, benefiting from the votes transferred from other parties/candidates and nonvoters. Their original model consists of two components. The first component includes turnout and vote counts under condition of fair elections. Vote counts are simulated from a normal distribution with the mean and standard deviation obtained from the area on the left-hand side of the mean. The second component accounts for intensity of anomalies allegedly linked to electoral frauds, and is obtained from the right-hand side of the sample mean. The model is used to obtain two fraud parameters: *incremental fraud*, measuring the transfer of moderate votes proportions, and *extreme fraud*, showing the extreme cases of votes transfer of votes inside the precinct. Each of the parameters are tied to different mechanisms. Ballot switching is reflected in *incremental fraud*, and and ballot stuffing is indicated by *extreme fraud*.

Specifically, Klimek's approach, according to Mebane (2016), suggests that both sample turnout and the winner's vote proportion are drawn from two normal distributions: $\tau_i \sim \mathcal{N}(\tau, \sigma_\tau)$ and $\nu_i \sim \mathcal{N}(\nu, \sigma_\nu)$. The occurrence of fraud corresponds to two conditions: (a) x^α the proportion of opposition votes going to the winner, and (b) $(1-y)^\alpha$ the proportion of genuine opposition votes going to the winner. Here α indicates whether more vote stealing or more vote manufacturing takes place. If $\alpha = 1$ both types of election fraud equally affect votes; if $\alpha < 1$ the vote stealing is important, whereas $\alpha > 1$ then vote manufacturing votes from nonvoters is prevalent.

Incremental fraud is presented by the proportion of nonvotes turned into votes for the winner f_i. The number of of votes going to the winning party through incremental fraud is $W_i = N_i(\tau_i \nu_i + x_i(1-\tau_i) + x_i^\alpha(1-\nu_i)\tau_i$, the number of votes for the opposition is $O_i = N_i(1-x_i^\alpha)(1-\nu_i)\tau_i$, and the number of nonvoters is $A_i = N_i(1-x_i)(1-\tau_i)$. Here is

$x_i \sim |\mathcal{N}(0, \theta)|$.

Extreme fraud, f_e, implies the probability proportion of nonvotes that are not turned into votes: $y_i \sim |\mathcal{N}(0, \sigma_v)|$, $\sigma_x = 0.075$, $0 < y_i < 1$. Consequently, $W_i = N_i(\tau_i \nu_i + (1 - y_i)(1 - \tau_i) + (1 - y_i)^\alpha (1 - \nu_i)\tau_i$, the number of votes for the opposition is $O_i = N_i(1 - (1 - \tau_i)^\alpha)(1 - \nu_i)\tau_i$, and the number of nonvoters is $A_i = N_i y_i (1 - \tau_i)$.

Finally, if fraud never occurs $f_0 = 1 - f_i - f_e$, then the number of votes for the winner is $W_i = N_i \tau_i \nu_i$, the number of votes for the opposition is $O_i = N_i \tau_i (1 - \nu_i)$, and the number of nonvoters $A_i = N_i(1 - \tau_i)$

The proposed model enables the authors to estimate the large presence of frauds in non-democracies, such as Uganda and Russia, vis-a-vis democracies, where no anomalies attributed to frauds are detected. The basic assumption of the model is partly supported by the data: the log transformed distributions of vote counts and turnout must look approximately Gaussian for the countries with fair elections. In contrast, for the countries with rigged elections, these distributions are characterized by right-tailed skewness and larger kurtosis. Even though the model is flexible across different levels of data aggregation, the measures of anomalies can be affected by the data heterogeneity. For instance, the authors' claim that extreme fraud with substantial fraction of districts reporting a 100% turnout with almost all votes going to a single party can be explained by specifics of precincts located in small rural communities, military units or prisons.

Overall, the frauds measurement model proposed in the paper of Klimek et al. (2012) is both innovative and contributing to the field of election forensics. Even though basic assumptions of the model are too strong, these are justified by the benefits of the model in estimation of anomalies and new opportunities of practical application of the model on a larger set of countries.

Mebane (2016), based on Klimek et al. (2012), further develops the model by utilizing a finite mixture likelihood model with three distinct components: probabilities of incremental fraud, extreme fraud and no fraud for each precinct. The model fitting is based on the likelihood function with variables treated from Klimek et al. (2012) as unobserved. The model assumes that τ_i, ν_i, x_i and y_i are generated from the normal distributions:

$$F(\mathbf{W},\mathbf{O},\mathbf{A} \mid \mathbf{N};\boldsymbol{\Psi}) = \sum_{j\in\{0,i,e\}} f_j \prod_{i=1}^{n} g_{jW}(W_i \mid N_i;\Psi)g_{jA}(A_i \mid N_i;\Psi) \tag{2.1}$$

In the model f_0, f_i and f_e are probabilities of no fraud, incremental fraud and extreme fraud, where $f_0 + f_i + f_e = 1$. The model describes the joint density of the observed vote counts for the winning party W_i, the observed sum of votes cast for all other parties O_i and the number of observed nonvotes A_i, i.e. $(W_i;O_i;A_i)$ as being conditioned on the number of eligible voters in each precinct N_i and estimated parameters $\boldsymbol{\Psi} = (\alpha,\nu,\tau,\sigma_\nu,\sigma_\tau,\phi)'$ defined by Klimek's model. The estimated precinct-level parameters are α – intensity of incremental fraud, ν – the winner's vote proportion and its standard deviation σ_ν, τ – the turnout and its standard deviation, and θ – incremental fraud garnering a higher number of votes for the leading party. The analytic integration of the finite mixture estimates with the estimates computed from alternative data sources, such as election monitoring reports or postelection complaints, provide the most fruitful strategy of election forensics research (Mebane 2016).

The model's parameters are estimated using an EM algorithm. In addition to it, several quantities of interest are computed: a) the magnitude of the frauds as the number of fraudulent votes; b) the precinct-level probability that election fraud occurs; c) the precinct-level magnitude of the frauds as the number of fraudulent votes (Mebane 2016). While the EM algorithm allows to obtain estimates of the conditional probability that each observation belongs to different fraud mechanisms, it doesn't provide the uncertainty of precinct-level probabilities. Moreover, similar to the Klimek's model, the finite mixture model also relies on multimodality in the distributions of turnout and vote proportions as the feature of election fraud, whereas multimodality can be also generated by the normal features of politics, for instance, strategic voting. Since reliance on the multimodality assumption can potentially lead to false positives, the use of contextual and auxiliary information can be crucial in determining the origin of electoral anomalies in specific context.

2.4 Context and Data

Russia has a long history of fraudulent elections in which artificial electoral support is provided by Kremlin-backed presidential candidates or parties, and viable political competition is rigidly suppressed. In the 2000s the growing authoritarian tendencies in Russian political system has exacerbated the problem of blatant election fraud and various electoral manipulations even further, making it an interesting subject of research by many scholars. The detrimental quality of Russian elections is analyzed in a large body of literature (Buzin & Lubarev 2008; Mebane 2010; Mebane & Kalinin 2009a; Myagkov et al. 2009; Shpilkin 2011), exposing numerous statistical anomalies across different electoral cycles and across different election administration levels.

The 2011-2012 electoral cycle was marked by the transition of presidential power from Dmitry Medvedev back to Vladimir Putin. In the fall 2011 then-President Medvedev proposed then-Prime Minister Vladimir Putin to run for a third term. This pre-arranged move of two politicians ignited a widespread public discontent and has set the tone for both upcoming Russian parliamentary and presidential elections. The parliamentary elections led to a crushing defeat of the party of power United Russia, which lost its two-thirds constitutional majority it had held prior to the election in spite of the manipulated character of elections and numerous fraud allegations. Consequently, obvious unfairness and uncleanness of election results provoked the rise of massive protests in Moscow and St. Petersburg, which forced the Kremlin to urgently launch a series of reforms aimed to provide electoral transparency of the forthcoming March presidential elections, such as installation of transparent ballot boxes(one-third of polling stations used transparent ballot boxes) and web cameras in every polling station across the country. Noteworthy, that alongside to the protests, both elections, especially presidential ones were marked by a significant increase in civic engagement, including an increased focus on election observation to enhance the integrity of the process: “Golos”, “Citizen-Observer”, “League of Voters”. The preventive actions of Russian electoral authorities to equip the precincts with the web cameras and transparent ballot boxes, along with the civic engagement in election observation helped to obtain auxiliary data on web-cameras and observers for our scholarly research.

Based on multiple sources, such as electoral, survey data and observer reports both Russian elections are seen as marked by widespread fraud significantly affecting the electoral outcomes (Enikolopov et al. 2013; Kalinin & Shpilkin 2012; Kobak et al. 2012). According to the findings, in 2012 the estimated election fraud in Russia amounts to 5% and 10% for Putin’s electoral support and turnout, respectively (Kalinin & Shpilkin 2012); other studies provide the estimated proportion of precincts with the election fraud, reaching about 40% in 2012 and 60% in 2011 (Klimek et al. 2012). It’s pretty difficult to argue about trustworthiness of Shpilkin’s or Klimek’s methods, since both rely on a certain set of assumptions. Specifically, these two approaches have two weaknesses: first, they are both highly sensitive to the algorithm by which the highest mode is identified; second, observed multimodality can be attributed to the electorate’s heterogeneity and differences in electoral behavior of the voters across the parties. However, by all accounts 2011 elections compared to 2012 elections are characterized by greater amounts of election fraud.

Luckily, availability of alternative data sources, such as the data on election observation and installation of electronic voting machines, makes the Russian case valuable for the methodological validation of a new measure. First, it’s assumed that the mere physical presence of observers putting election administrators under scrutiny will most likely change their behavioral strategies and prevent them from committing election fraud. Second, the installation of electronic voting machines in selected precincts makes traditional manipulation, such as ballot stuffing or ballot switching, immensely costly for election administrators, subsequently resulting in a reduction electoral malfeasance. The installation of web cameras can also impact the behavioral strategies of administrators by constraining their traditional vote manipulation strategies. Both approaches work well under the assumption that we randomly assign precincts to receive treatment or not, i.e. allowing randomization to balance out possible confounders across treatment and control groups. Thereby, this is a convenient way to assess the magnitude of electoral frauds free from distribution assumptions and receive a useful instrument for validation of the finite mixture estimator.

Since we deal with the observational data rather than experimental data here we need to account for the differences in observed covariate distributions between our treatment and control groups. Moreover, it is also assumed that observers or installation of voting machines wouldn't be altering the voter's behavior. It can be the case, that the voters will be viewing their voting choice as being monitored, especially, knowing that certain features of KOIBs/KEGs imply creation of a file with a picture of the bulletin with the time stamp (Herron 2009). Even though the placement of web cameras is expected to yield more information about the cleanness of election results, due to their installation in almost all polling stations in 2012 and the lack of control group, it is impossible to derive any estimate of election frauds. Therefore, the use of another treatment based on variability of utilized voting machines across the precincts sounds more promising.

In my analysis of 2011 elections I'll be using the dataset on election observation in Moscow previously analyzed in Enikolopov et al. (2013), available through Vasily Korovkin. The data originally comes from the independent nongovernmental organization Citizen Observer (Grazhdanin-nablyudatel'), that trained more than 500 volunteer observers in the city of Moscow. The observers were sent to 156 randomly selected polling stations using a systematic sampling technique (Levada Center). Enikolopov et al. (2013) conclude that the mere presence of observers reduced the share for United Russia by 9.3-

10.8 percentage points and increased it for other parties. In my 2012 analysis I'm using the data from the website of SMS-CIK project, which allowed the observers to promptly report their information from the precinct-level protocols. The procedure is rather simple: the phone messages containing the figures from precinct-level protocols are texted by observers to a specific phone number, then they are processed by the servers and instantly become publicly available through the website *www.sms-cik.org*. Unfortunately, this procedure implies that election observers are self-selected into the database rather than randomly assigned to precincts by design. These data have been downloaded from the website, parsed and merged with the official electoral precinct-level 2012 data set.

The geographical data and voting equipment data on both elections has been kindly provided by Sergey Shpilkin. In both the 2011 and 2012 elections two types of new voting machines were used. The first, KOIB (Kompleks Obrabotki Izbiratel'nykh Byulleteney), is an optical scan voting machine with a ballot box made of translucent materials. As one of its features, it creates a time-stamped file of the scanned ballot, and transmits election results over telecommunications network to a higher level of election commission (it's an integral part of the GAS Vybory automated tabulation system). The second, the KEG (Kompleks Elektronnogo Golosovaniya) is a direct-recording electronic (DRE) voting machine with a touch-screen with lists of candidates and parties for the voter to choose from. Its results are stored in the memory of KEG, as well as printed on a special paper tape unavailable to the voter. Both devices can induce election administrators to abstain from traditional election fraud, such as ballot stuffing and ballot switching (See Figure A.1(a),(b) in Appendix A).

Bader (2013), by applying difference-in-difference design based on the Myagkov et al. (2009)'s idea of "flow of votes" between the elections, finds that for precincts equipped with KOIBs in 2011 but not in 2012 are characterized by decreased turnout (-3.8%) and incumbent's vote share (-4.8%). For the precincts equipped with KOIBs in 2012 but not in 2011, the effects of KOIBs are small and insignificant amounting to only 0.4% for turnout, and 0.6% for the incumbent's support. Since the selection criteria for placing KOIBs/KEGs are vaguely known (for instance, KEGs are predominantly used in ethnic regions as a bilingual device), it is hard to draw stronger statistical inferences using Bader (2013)'s findings. As a part of solution to this problem in this paper the polling stations will be matched to approximate random assignment of the treatment (Herron 2010; Sjoberg 2014). Unfortunately, proposed matching procedure does not necessarily solve many of the problems associated with non-random assignment and the absence of pre-treatment data.

Hence, my validation study will be build on the analysis of the following datasets:

- Precinct-level electoral data used for estimation of election forensics measures of fraud, including the finite mixture model;
- Data on election observation in Moscow (parliamentary elections 2011) and nation-wide (presidential elections, 2012);
- Data on the allocation of KOIBs/KEGs/observers in 2011 and 2012 elections.

2.5 Analytic Strategy

My analysis is built on the quasi-experimental data using propensity score matching technique, correlation analysis and a geographic cluster analysis of election forensics estimates. My analytic strategy implies: (1) validation of the finite mixture model's estimates using the quasi-experimental data on election observation and allocation of KOIBs/KEGs; (2) validation of the finite mixture model's estimates using geographic distribution of election fraud described in theoretical literature.

2.5.1 Validation Using Quasi-Experimental Data

Since no data are available to solve the problems associated with non-random assignment of the treatment, here I apply to propensity score matching. The result of the matching procedure, which was carried out with *Matching()* package (Sekhon 2012) in **R**, is a dataset balanced in key variables: type of the region (Republic/Oblast), urban/rural, precinct size. Originally, my top priority was given to matching between the pairs of precincts with observers/voting machines and precincts without observers/paper ballots boxes based on the k-nearest neighbors algorithm, however, large standard errors prevented me from pursuing this approach any further. The choice of variables included in propensity score model are related to the outcome. Republics usually tend to exhibit more electoral support for authorities compared to oblast's. Moreover, the empirical evidence suggests that Republics compared Russian oblast's, by having better established "machine politics" in place, are able to achieve unprecedented levels of electoral mobilization (Kalinin & Mebane 2013; Mebane & Kalinin 2009a). Here "machine politics" implies the creation of organizations, i.e. "political machines" providing electoral support by trading material benefits to citizens in exchange for their votes (Golosov 2013). As a rule, these organizations are located in ethnic republics and autonomous districts with dense ethnicity-based social networks and rural areas with the rural population dependent on local bosses (Golosov 2013; Hale 2003; Matsuzato 2000).

Arbatskaya (2004) by analyzing Russian elections 1996-2000 argues that there is substantial variation in political participation across the regions, which is partly determined by administrative interference in the electoral process by officials as well as other factors, which include the type of the region, urban/rural settlement, type of industrial structure, seasonal effects contributing to the changes in turnout rates during the day. As a result of her analysis, Arbatskaya groups regions into two broad categories of turnout activity: passive, predominantly, Russian regions and urban territories; and active regions, Republics and rural territories.

Hence, by including three precinct-specific variables (type of the region, urban/rural, precinct size) into my propensity score model I hope to account for heterogeneity of electoral practices across various levels of aggregation.

2.5.2 Validation Using Geographic Distribution of Election Fraud

For Russia, expected geographic distribution of election fraud is closely connected to the strength of political machines in the regions. Hale (2003) argues that the ability of regional governors to convert patronage networks into political machines aimed to provide necessary level of incumbent's electoral support has been the case in the 2000s. The use of "administrative resource" implies that "different kinds of pressures are exerted upon voters by the regional authorities in order to provide desired electoral returns" (Golosov 2006). In the post-Soviet years the Republics enjoyed more bargaining power with the Center (See next Chapter) and used to be more capable to manipulate voting in the regions (Reisinger & Moraski 2017; Solnick 1995). The governors in the Republics were more effectively monitoring voting than their counterparts from the Russian regions, and thus were able to punish or reward voters more effectively (Hale 2007, 231). Hence, here we would expect that locations associated with Republics and regions with strong political machines will most likely exhibit largest clusters of election fraud.

Which regions will most likely exhibit the fraudulent clusters? The list of such regions can be derived using the expert ratings of regional democracy constructed by Nikolay Petrov and Alexey Titkov (Petrov & Titkov 2013). These regions in descending order of democracy are Dagestan Republic , Omskaya oblast', Orlovskaya oblast', Tambovskaya oblast', Karachaevo-Cherkessiya Republic, Yamalo-Nenetskiy autonomous okrug, Kostromskaya oblast', Penzenskaya oblast', Tatarstan Republic, Yakutiya Republic, Bryanskaya oblast', Rostovskaya oblast', Smolenskaya oblast', Khakassiya Republic, Adygeya Republic, Belgordskaya oblast', Mariy El Republic, Bashkortostan Republic, Kemerovskaya olbast', Kurganskaya oblast', Tyva Republic, Kalmykiya Republic, Severnaya Osetiya Republic, Kurskaya oblast', Kabardino-Balkariya Republic, Ingushetiya Republic, Mordoviya Republic, Chukotka autonomous okrug and Chechnya Republic. Hence, if our finite mixture estimates account for the poor democratic environment and the presence of the strong regional machines, we would expect to find the majority of clusters are located in these listed regions.

It is also expected that the clusters of election fraud will be associated with the rural areas where higher levels of social connectivity and lower levels of anonymity compared to urban area predispose the use of local political machines. Reisinger and Moraski (2017) argue that local politicians who play prominent role in the provision of goods and services will be the most successful in mobilizing voter support in their respected localities. The literature suggests that rural social networks are effective in mobilization of voter support in Kyrgyzstan (Darr & Hesli 2010) and rural Africa (Kuenzi & Lambright 2011). Hence, we would expect that rural localities will be most likely to exhibit clusters of election fraud.

This part of my analysis adopts geographic clustering tests, indicating geographical clustering patterns across different election forensics measures at the level of precincts and territories. Geographic clustering indicates whether any clusters or localities share similar strategies of election administrators. While the precinct-level analysis provides us with the most detailed overview of fraud's allocation in specific localities, the territory-level analysis helps to derive aggregated measures of election fraud at the level of Russian territories.

The presence of clustering doesn't necessarily imply the possibility of fraud but can be attributed to a large range of causes. However, we may have reason to believe that there is some heterogeneity among certain precincts or territories related to variation in fraud. I use two estimation procedures available in the Election Forensics Toolkit: (a) Getis-Ord G_i analysis of hotspots (Ord & Getis 1995) to measure whether the mean of values geographically close to observation i differs from the global mean and (b) local Moran's I_i, which measures whether the value at observation i differs from the mean of values geographically close to the observation i (Anselin 1995). Both statistics are estimated for each election forensics indicator: precinct-level data in 2012 (Getis-Ord G_i) and territory-level data for 2011 and 2012 (local Moran's I_i). By doing so I am able to identify the levels at which the coordination of vote manufacturing and vote stealing is taking place and as a result better understand specifics of its organization. Moreover, at each selected level of analysis I employ correlation analysis between the hot spot types and test levels assigned to each polling station or territory.

If the finite mixture estimates reflect the same signaling mechanism as other election forensics measures, we would expect that our finite mixture estimates will be also associated with alternative measures of election fraud. Using these measures in the model we will be able to examine the finite mixture's construct validity by tracking its relationship with other election forensics measures.

Hence, the proposed research hypotheses to be tested here:

Hypothesis 1. *The finite mixture indicator is expected to be affected by the presence of KOIBs/KEGs and well-trained observers, since more vote rigging is taking place in the polling stations equipped with the ballot boxes rather than KOIBs/KEGs and without well-trained observers vs. with them.*

Hypothesis 2. *The geographic clustering tests will expose the presence of election fraud clusters mainly located in the areas exhibiting poor democratic environment and the presence of the strong regional machines, these are mainly the Republics and the rural territories.*

Hypothesis 3. *The strong correlations between the geographic clusters of the final mixture estimates and the geographic clusters of alternative election forensics measures associated with signaling patterns ([P05] test for turnout and incumbent), and anomalous last digits in vote counts[CL] found at the levels of both precincts and territories, are expected to be found in our study.*

To test my proposed hypotheses, I turn to my empirical data analysis.

2.6 Findings

According to my findings at the Russian presidential elections about 8% of precincts host incremental fraud and about 0.2% – extreme fraud; at the Russian parliamentary election these figures are 11% and 0.2%, respectively. These findings match our initial expectations based on multiple accounts of extensive fraud in the parliamentary elections and reduced use of fraud in the presidential election. Thus, the finite mixture estimates demonstrate that 2011 Russian parliamentary elections are, indeed, far more fraudulent compared to presidential election. In terms of fraud probabilities, the finite mixture model provides us with more conservative estimates compared to Klimek's estimates yielding 64% of fraudulent precincts back in 2011 Duma elections, and 39% in 2012 presidential elections.

Furthermore, Mebane (2016, Table 4)'s estimates illustrate much smaller magnitudes of election fraud, amounting to 1.5% in the parliamentary elections and 0.68% in the presidential elections. Specifically, the estimates of the number of votes produced by incremental and extreme frauds (Mebane 2016, 13) show 680,082 (M_i) and 260,254 (M_e) fraudulent votes in 2011 Duma elections and 292,339 (M_i) and 189,912 (M_e) fraudulent votes in 2012 presidential elections (M_i and M_e are estimated numbers of votes produced by incremental and extreme frauds). These findings of fraud magnitudes are inconsistent with the previous studies yielding the magnitude of election fraud in the range between 5% and 10% (Kalinin & Shpilkin 2012). Similarly to the finite mixture probabilities, (Mebane 2016)'s estimates of the fraud's magnitude provide us with the most conservative estimates of election fraud.

Turning to a more detailed data analysis, Table 2.1 illustrates the effects of voting machines and observers on turnout and candidates' vote shares in 2012. In the context of this research the observed effects of technology on turnout and incumbent's support can be regarded as proxies for election fraud, since the installation of electronic voting machines in precincts makes traditional manipulation, such as ballot stuffing or ballot

Table 2.1: Effects of KOIBs/KEGs and Observers on Turnout and Vote Share, 2012

	KOIBs	KEGs	Observers	Violations
Putin	-0.036***	0.035**	-0.087***	0.011
	(0.002)	(0.012)	(0.003)	(0.014)
Zhirinovsky	-0.001	-0.007*	-0.005***	-0.006
	(0.001)	(0.003)	(0.001)	(0.004)
Zuganov	0.008***	-0.027***	0.004*	-0.011
	(0.001)	(0.006)	(0.002)	(0.008)
Prohorov	0.02***	0.009*	0.074***	-0.003
	(0.001)	(0.004)	(0.002)	(0.014)
Turnout	-0.003	0.054***	-0.019***	-0.012
	(0.002)	(0.011)	(0.003)	(0.014)
f_i	-0.006*	-0.053*	-0.007^{x}	-0.024
	(0.003)	(0.022)	(0.004)	(0.025)
f_e	-0.002*	0.042***	-0.001	0.000
	(0.001)	(0.011)	(0.001)	(0.000)
Observations	5241	311	1819	54

Notes: Matching is based on a set of observables: number of registered voters, residence (urban/rural), region (republic/oblast').
Data: Precinct-level electoral data merged with the data on KOIBs/KEGs and election observation (number of matched units is provided in *Observations*).
Variables: Listed variables show the difference in vote shares for each candidate, turnout and the finite mixture model's estimates between KOIB-equipped precincts vs. precincts with ballot boxes ("KOIBs"), KEG-equipped precincts vs. precincts with ballot boxes ("KEGs"), precincts with observers vs. precincts without observers ("Observers"), precincts with violations vs. precincts without detected violations ("Violations"). "Putin", "Zhirinovsky", "Zuganov" and "Prohorov" variables stand for the differences in vote shares for Vladimir Putin, Vladimir Zhirinovsky, Gennadiy Zuganov and Mikhail Prokhorov, respectively.
Significance levels: $^{x}p \leq 0.1$, *p ≤ 0.05, **p ≤ 0.01, ***p ≤ 0.001.

switching, immensely costly for election administrators.

As mentioned earlier, in order to reduce potential biases due to nonrandom assignment, propensity score model was utilized based on a number of covariates, such as the number of registered voters, residence (urban/rural) and region (republic/oblast'). Unsurprisingly, the effect of optical scan voting machines (KOIBs) on turnout and Putin's vote count is negative, reducing incumbent's support by 3.6 percentage points, while for other candidates it remains positive or statistically insignificant. In other words, compared to KOIBs, ballots boxes seem to provide Putin with statistically significant inflated support allegedly linked to election fraud. Both our finite mixture measures f_i and f_e are consistent with our expectations, indicating statistically significant negative effects of KOIBs: −0.6 and −0.02 percentage points, respectively. KEGs demonstrate more mixed findings: this technology results in inflation of 3.5 percentage points in Putin's vote share, which is visibly connected to the similar magnitude of extreme fraud f_i, i.e. stealing votes (+4 percentage points). It also seems that the presence of observers decreases Putin's support by 9 percentage points and turnout, i.e. ballot stuffing, by about 2 percentage points with marginally significant f_i. Finally, detection of violations by observers seems to exercise no effects on turnout or vote shares of interest. One of the explanations behind KEGs exhibiting higher levels of election fraud compared to the ballot boxes is their small size and mobility making it possible to use it in small localities or the rural areas with higher levels of social connectivity and lower levels of anonymity. Moreover, the use of KEGs in remote areas is correlated with the lack of proper election observation and elevated likelihood of electoral malfeasance.

Similar findings are derived from Table 2.2: the presence of KOIBs yields a positive effect on vote shares for almost all the parties, but negative effect on United Russia's vote share as well as turnout reducing each of these estimates by 6.7 and 2 percentage points, respectively. The statistics of incremental fraud f_i demonstrates a reduction in the estimate by 4 percentage points. In contrast, again, KEGs positively affect United

Table 2.2: Effects of KOIBs/KEGs on Turnout and Vote Share, 2011

	KOIBs	KEGs
Just Russia	0.022⋆⋆⋆	-0.018⋆⋆
	(0.001)	(0.006)
LDPR	0.009⋆⋆⋆	-0.006
	(0.001)	(0.006)
Patriots	0.002⋆⋆⋆	0.001
	(0.000)	(0.001)
KPRF	0.019⋆⋆⋆	-0.032⋆⋆⋆
	(0.002)	(0.008)
Yabloko	0.012⋆⋆⋆	0.004⋆
	(0.001)	(0.002)
Pravoe delo	0.001⋆⋆⋆	0.001⋆⋆⋆
	(0.000)	(0.000)
United Russia	-0.067⋆⋆⋆	0.061⋆⋆
	(0.003)	(0.02)
Turnout	-0.019⋆⋆⋆	0.074⋆⋆⋆
	(0.003)	(0.014)
f_i	-0.039⋆⋆⋆	0.055⋆
	(0.004)	(0.027)
f_e	-0.001	0.006
	(0.001)	(0.005)
Observations	4818	301

Notes: Matching is based on a set of observables: number of registered voters, residence (urban/rural), region (republic/oblast').
Data: Precinct-level electoral data merged with the data on KOIBs/KEGs and election observation (number of matched units is provided in *Observations*).
Variables: Listed variables show the difference in vote shares received by each party, turnout and the finite mixture model's estimates between KOIB-equipped precincts vs. precincts with ballot boxes ("KOIBs"), KEG-equipped precincts vs. precincts with ballot boxes ("KEGs"). "United Russia", "Just Russia", "LDPR", "Patriots", "KPRF", "Yabloko" and "Pravoe delo" variables stand for the differences in vote shares received by different parties.
Significance levels: $^{\times}p \leq 0.1$, $^{\star}p \leq 0.05$, $^{\star\star}p \leq 0.01$, $^{\star\star\star}p \leq 0.001$.

Russia's vote share and turnout, inflating them by 6 and 7.4 percentage points each with the magnitude of incremental fraud f_i reaching 5.5 percentage points. This observation supports our claim that a different mechanism of election fraud tends to be associated with KEGs rather than KOIBs, and it holds across the elections.

My analysis of 2012 presidential elections on the Moscow level demonstrates that while KOIBs seem to exercise no effect on Putin's support, they do seem to reduce turnout by 6 percentage points and incremental fraud by 12 percentage points. While the presence of observers seems to contribute to a drop in Putin's support by 2 percentage points and Prokhorov's support by 2 percentage points, none of the forensics measures demonstrates statistical significance. Finally, detection of violations does not seem to have any statistically significant impact.

Turning to analysis of parliamentary elections in Moscow, we find more evidence of blatant fraud (See Table 2.4). KOIBs seem to have reduced United Russia's support by as much as 19 percentage points and turnout by almost 12 percentage points, whereas the electoral support for other participating parties has clearly increased. The measure of incremental fraud has been also reduced by 11 percentage points. The presence of observers demonstrates a similar pattern of effects, resulting in a drop in support for United Russia by almost 11 percentage points and turnout by 6.4 percentage points. More importantly, however, the presence of observers has a negative effect on incremental fraud, reducing it by almost 5 percentage points. Finally, the detection of violations impacted the measure of turnout and incremental fraud, reducing both measures by almost 3 percentage points.

Thus, **Hypothesis 1** is partly supported by my analysis: in Russia, more vote rigging is taking place in the polling stations equipped with ballot boxes rather than KOIBs, and without well-trained observers rather than with them. The measure of incremental fraud seem to almost always agree with this observation, showing statistical significance with expected signs and magnitude for effects. Another distinctive finding of my analysis is that a different underlying mechanism of election fraud related to KEGs seems to be

Table 2.3: Effects of KOIBs and Observers on Turnout and Vote Share, Moscow 2012

	KOIBs	Observers	Violations
Putin	-0.008	-0.021***	-0.028
	(0.007)	(0.002)	(0.02)
Zhirinovsky	0.003	-0.003***	0.002
	(0.002)	(0.001)	(0.005)
Zuganov	0.005^{x}	0.003***	-0.001
	(0.003)	(0.001)	(0.007)
Mironov	-0.001	0.002***	0.005^{x}
	(0.001)	(0.000)	(0.003)
Prohorov	0.013**	0.02***	0.02
	(0.005)	(0.002)	(0.017)
Turnout	-0.055***	0.004	-0.022
	(0.01)	(0.003)	(0.023)
f_i	-0.12***	-0.003	-0.053
	(0.018)	(0.004)	(0.051)
f_e	-0.004	0.000	0.000
	(0.003)	(0.000)	(0.000)
Observations	253	942	17

Notes: KOIBs(matched), Observers (matched), Violations (matched). Matching is based on a set of observables: number of registered voters, votes reported at different times during the day.
Data: Precinct-level electoral data merged with the data on KOIBs/KEGs and election observation (number of matched units is provided in *Observations*).
Variables: Listed variables show the difference in vote shares for each candidate, turnout and the finite mixture model's estimates between KOIB-equipped precincts vs. precincts with ballot boxes ("KOIBs"), KEG-equipped precincts vs. precincts with ballot boxes ("KEGs"), precincts with observers vs. precincts without observers ("Observers"), precincts with violations vs. precincts without detected violations ("Violations"). "Putin", "Zhirinovsky", "Zuganov" and "Prohorov" variables stand for the differences in vote shares for Vladimir Putin, Vladimir Zhirinovsky, Gennadiy Zuganov and Mikhail Prokhorov, respectively.
Significance levels: $^{x}p \leq 0.1$, *p ≤ 0.05, **p ≤ 0.01, ***p ≤ 0.001.

Table 2.4: Effects of KOIBs and Observers on Turnout and Vote Share, Moscow 2011

	KOIBs	Observers	Violations
Just Russia	0.047***	0.022***	0.002
	(0.003)	(0.004)	(0.005)
LDPR	0.051***	0.017***	0.003
	(0.003)	(0.003)	(0.006)
Patriots	0.005***	0.002***	-0.001
	(0.001)	(0.000)	(0.001)
KPRF	0.061***	0.028***	-0.001
	(0.005)	(0.004)	(0.008)
Yabloko	0.035***	0.035***	0.009
	(0.004)	(0.004)	(0.007)
Pravoe delo	0.003***	0.001***	0.000
	(0.000)	(0.000)	(0.001)
United Russia	-0.193***	-0.108***	-0.019
	(0.012)	(0.011)	(0.016)
Turnout	-0.118***	-0.064***	-0.027^x
	(0.01)	(0.008)	(0.016)
f_i	-0.111***	-0.045***	-0.034**
	(0.015)	(0.008)	(0.012)
f_e	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Observations	250	3163	3163

Notes: KOIBs(matched), Observers (not matched), Violations (not matched). Matching is based on a set of observables: number of registered voters, votes reported at different times during the day.
Data: Precinct-level electoral data merged with the data on KOIBs/KEGs and election observation (number of matched units is provided in *Observations*).
Variables: Listed variables show the difference in vote shares received by each party, turnout and the finite mixture model's estimates between KOIB-equipped precincts vs. precincts with ballot boxes ("KOIBs"), KEG-equipped precincts vs. precincts with ballot boxes ("KEGs"). "United Russia", "Just Russia", "LDPR", "Patriots", "KPRF", "Yabloko" and "Pravoe delo" variables stand for the differences in vote shares received by different parties.
Significance levels: $^x p \leq 0.1$, $^\star p \leq 0.05$, $^{\star\star} p \leq 0.01$, $^{\star\star\star} p \leq 0.001$.

occurring: most likely the use of this device in remote areas makes it more susceptible to election fraud compared to KOIBs.

Next, I present the results from hot spot analysis of Russian 2012 elections based on the G_i statistic computed using multiple election forensics indicators. The maps display the "hotspots" of anomalies, indicating whether the mean of values geographically close to a particular observation differs from the overall mean. The red spots in Figure 2.1(a) indicate whether there are clusters of atypically high values, i.e. locations where the local mean of the variable of interest is significantly greater than the overall mean value $\bar{f}_i = 0.08$. Many red spots are clumped together geographically in predominantly ethnic regions, such as Tatarstan, Bashkortostan, Mordoviya, Chuvashiya, Dagestan, Chechnya, as well as some Russian oblast's: Belgorodskaya and Voronezhskaya oblast's and several others, indicating high levels of incremental fraud probabilities. Detailed information on the number of territories and precincts belonging to anomalous clusters is provided in Table A.1 of Appendix A. The predominance of blue colored spots, indicating local average scores being significantly below the overall average, are noticeably concentrated in the Moscow region and the capital.

Separately built cluster maps for Moscow's voting in 2011 and 2012 elections do not seem to reveal any interesting patterns related to anomalies in respective elections (See Figure A.2). The hotspots for Moscow 2012 elections demonstrate the lack of heterogeneity in the values of clusters. Most precincts are blue colored, thus indicating that compared to Russia's global mean of 0.08, the majority of Moscow's precincts exhibit low values of fraud. Hence, in accordance with our expectations even though 2011 and 2012 elections in Moscow seem to be affected by election anomalies, the Moscow's case seems to be not too far away from the fraud's national average.

Figure 2.1(b) illustrates that the clusters of extreme fraud significantly higher than the global mean are mostly located in Chechnya and in the northern part of Dagestan, with smaller clusters located in Tatarstan. While Figure 2.1(c) does not show much evidence of localized anomalies in Putin's vote counts [CL] against the global mean $\overline{CL} = 4.48$, as it is in close proximity to theoretical expectation, Figure 2.1(d) demonstrates tiny clusters scattered around the blue background with the clumps of red points located in the northern part of Dagestan (all compared to the global mean of $\overline{P05} = 0.21$). Anomalies in turnout display similar findings. In Figure 2.1(e), a small blue cluster is noticeable in the Tatarstan region. However, in Figure 2.1, the global mean is elevated, informing us that anomalies of turnout are widespread in Russia. In this sense, Tatarstan looks uniquely "deflated". Finally, Figure(f) shows that red-colored signaling patterns occur in mostly Tatarstan and in the southern Dagestan exceed the global mean of $\overline{P05} = 0.22$.

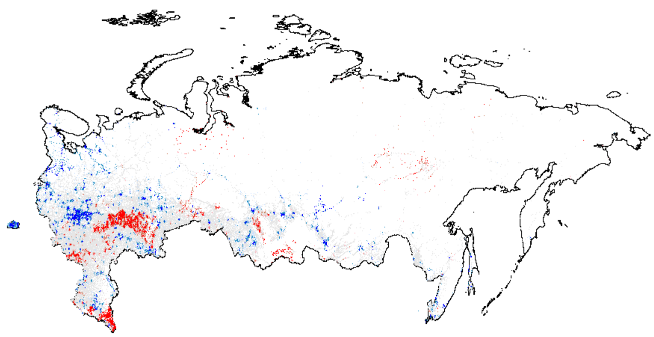
The results for Russian parliamentary elections are demonstrated in Figure 2.2. Since some of the regions changed enumeration of their precincts between the elections in 2012 for which the geodata is available) compared to 2011 (for which there is insufficient geo data), I removed those regions from my 2011 clustering analysis. As a result, omitted regions are visible as blank spots on 2011 maps. Nevertheless, my findings still demonstrate that the geographical patterns of election forensics yield surprising consistency across both studied elections, even against somewhat elevated global means for 2011 due to higher levels of electoral anomalies in that year.

As we earlier hypothesized, across different years the clustering patterns are located in a subset of listed regions, such as Dagestan Republic, Tatarstan Republic, Belgorodskaya oblast', Bashkortostan Republic, Severnaya Osetiya Republic, Kabardino-Balkariya Republic, Mordoviya Republic, and, finally, Chechnya Republic. For several regions the finite mixture estimator in some disagreement with the democracy scores, these regions are Chuvashskaya Republic and Voronezhskaya oblast'.

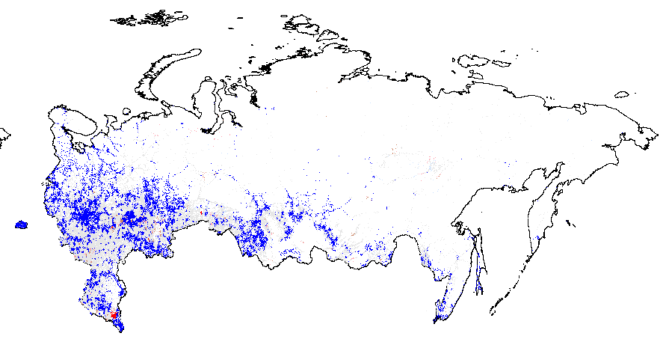
The finite mixture figures also demonstrate tiny dispersed clusters, which can be attributed to local political machines producing rigged election outcomes.

The next question addressed here relates to the check in geographical consistency between explored geovalues: if empirical association between these values exists than a sig-

Figure 2.1: Hotspot and Cluster Outlier Analysis of Forensics Indicators, Russia 2012, Getis-Ord G_i, Precinct-Level Data

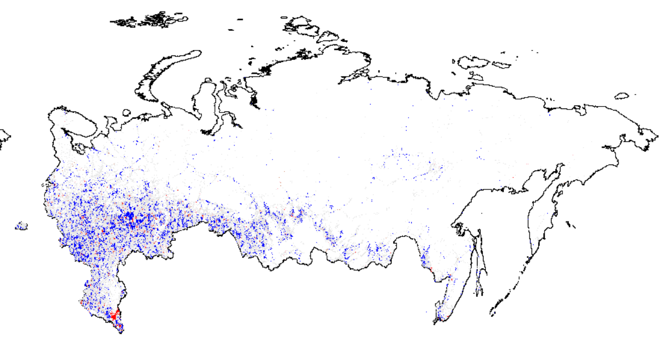


(a)



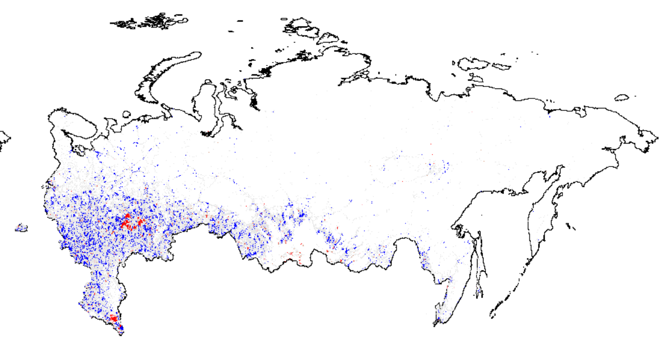
(b)

(c)



(d)

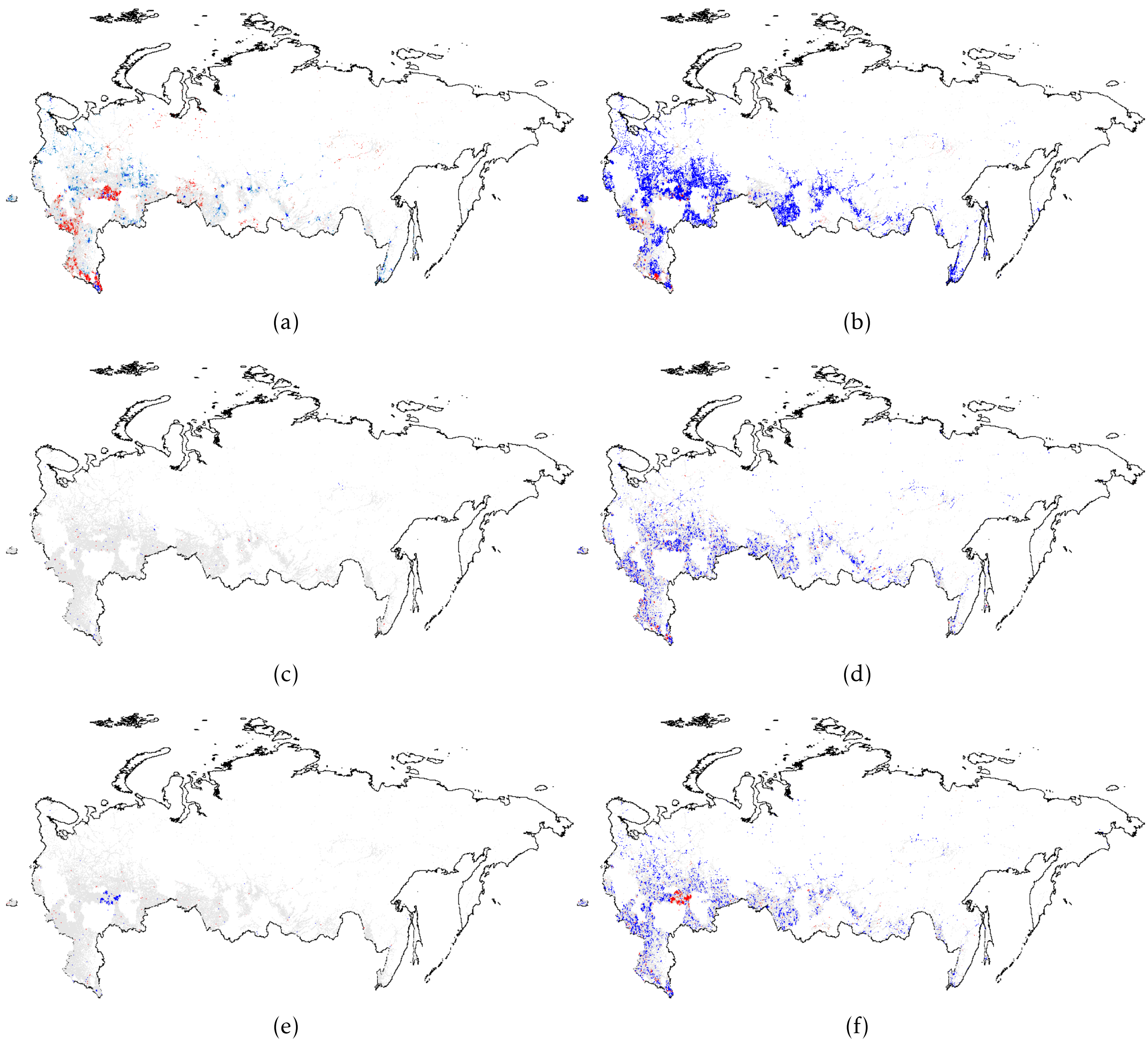
(e)



(f)

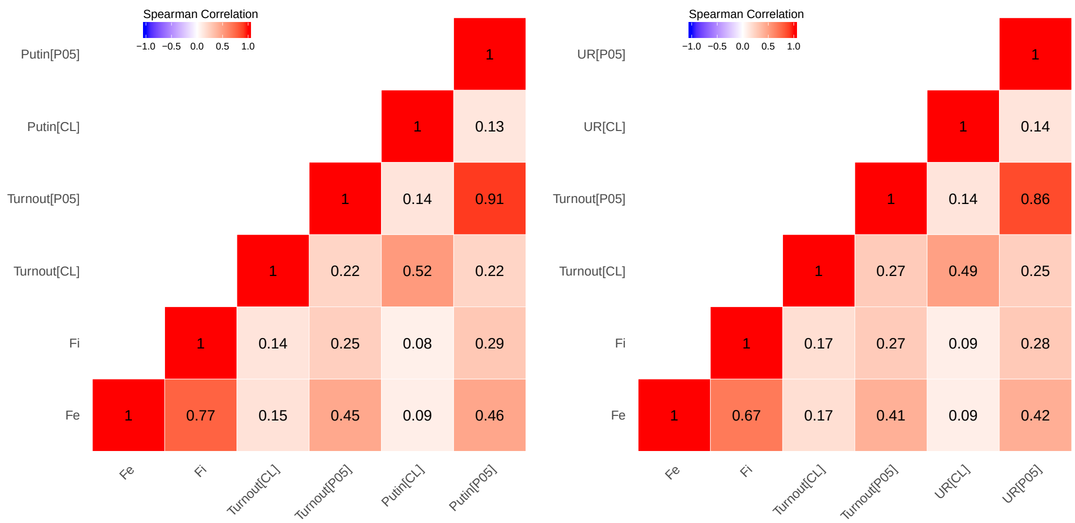
Notes: Overall fraud probability averages are in parentheses. (a) – f_i(0.08) ; (b) – f_e (0.002); (c) – Putin[CL](4.48); (d) – Putin[P05] (0.21); (e) – Turnout[CL] (4.939); (f) –Turnout[P05] (0.22).
Measures of anomalies: [P05] – 0s and 5s in the last digit of the turnout percentage and incumbent's vote percentage; [CL] – last digits in vote counts and turnout.

Figure 2.2: Hotspot and Cluster Outlier Analysis of Forensics Indicators, Russia 2011, Getis-Ord G_i, Precinct-Level Data



Notes: Overall fraud probability averages are in parentheses. (a) – f_i (0.11); (b) – f_e (0.002); (c) – UR[CL] (4.47); (d) –UR[P05] (0.21); (e) – Turnout[CL] (4.92); (f) –Turnout[P05] (0.22).
Measures of anomalies: [P05] – 0s and 5s in the last digit of the turnout percentage and incumbent's vote percentage; [CL] – last digits in vote counts and turnout.

Figure 2.3: Correlation Matrices for Precinct-Level Data, Getis-Ord G_i



(a) (b)

Notes: (a) – 2012 presidential elections; (b) – 2011 parliamentary elections.

naling mechanism of election fraud behind the finite mixture estimates can be uncovered (Kalinin & Mebane 2013). Figures 2.3 (a), (b) contain geographic correlation matrices between respective geovalues. The categorical variable was coded by assigning to each of the precinct categories different numeric code. In the cluster analysis we deal with four basic categories of precincts: "HH" – high value among high values of anomalies; "LL" – low value among low values of anomalies; "LH" – low value among high values anomalies; "HL" – high value among low values of anomalies) measured at $\alpha = 0.01$ or $\alpha = 0.05$ significance levels. The obtained categorical variable, which will be utilized in my correlation analysis, was coded as "-2" – LL,"-1" – HL, "0" – not significant, "1" – LH and "2" – HH. The rationale for building the variable's scale starting with cluster's low value among low values and ending with high value among high values is to express the relative strength of clustered election fraud across the precincts.

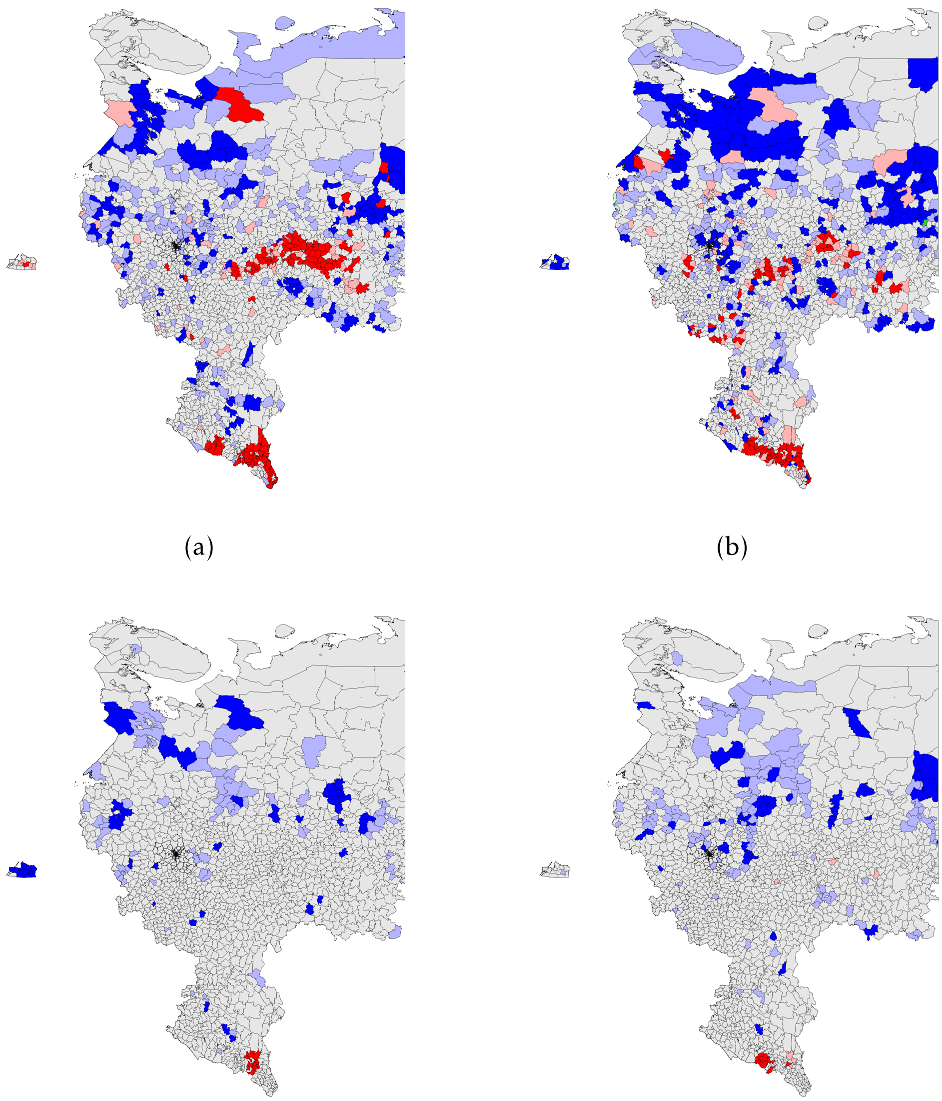
Our findings demonstrate that for both elections the correlations between the clusters associated with signaling patterns [P05] in Putin's/United Russia's vote shares and signaling patterns in Turnout [P05], on the one hand, as well as between estimated incremental

f_i and extreme frauds f_e, on the other hand, are specifically strong (ρ = 0.86 for 2011 elections; ρ = 0.91 for 2012 elections). While moderate correlation is observed between the clusters indicating extreme fraud and P05 in turnout (ρ = 0.41 for 2011 elections; ρ = 0.45 for 2012 elections) and UR's/Putin's electoral support (ρ = 0.42 for 2011 elections; ρ = 0.46 for 2012 elections), quite weak correlation persists between incremental fraud and our P05 indicator for UR's/Putin's electoral support(ρ = 0.28 for 2011 elections; ρ = 0.29 for 2012 elections) and turnout(ρ = 0.27 for 2011 elections; ρ = 0.25 for 2012 elections). This finding demonstrates that the geographic distribution of the finite mixture fraud probabilities can be also connected to the strength of political machines in the regions. Moreover, this finding is also backed by our expert evidence, showing that the list of the regions with the least democracy scores and strongest political machines matches partially matches the clusters of the finite mixture fraud probabilities.

On the next stage I employ hot spot analysis of Russian elections, by calculating the mean of precinct-level election forensics indicators for each territory, i.e. subregional administrative unit. This approach enables us to test if territory-level clusters in any particular way correlate with the findings based on the precinct-level data analysis. It also helps to test the hypothesis if the likelihood of election fraud can be attributed to the territorial level. Moreover, to dismiss the areas with low population density, here I intentionally resort to comparison of precinct-level clusters with the territory-level clusters, by presenting the map of western part of Russia for both estimated finite mixture measures.

The patterns associated with the territory-level analysis are similar to the patterns from the precinct-level analysis. In 2012 clusters of incremental frauds f_i are persistent predominantly in ethnic territories of Tatarstan, Bashkortostan, Mordoviya, Chuvashiya, Dagestan, Chechnya, Severnaya Osetiya, and of extreme fraud f_e, in Chechnya and Dagestan. In 2011 clusters of incremental fraud f_i are more dispersed involving, in addition to the previously mentioned regions, Amurskaya, Belgorodskaya, Voronezhskaya oblast's, Krasnodarskiy kray, and Karachaevo-Cherkessiya Republic and several others. Extreme

Figure 2.4: Cluster and Outlier Analysis for Russia 2011,2012, f_i, local Moran's I, Territory-Level Data



(a) (b) (c) (d)

Notes: Overall fraud probability averages are in parentheses. (a) – f_i 2012 (0.09); (b) – f_i 2011(0.13); (c) –f_e 2012 (0.002); (d) – f_e 2011 (0.003).

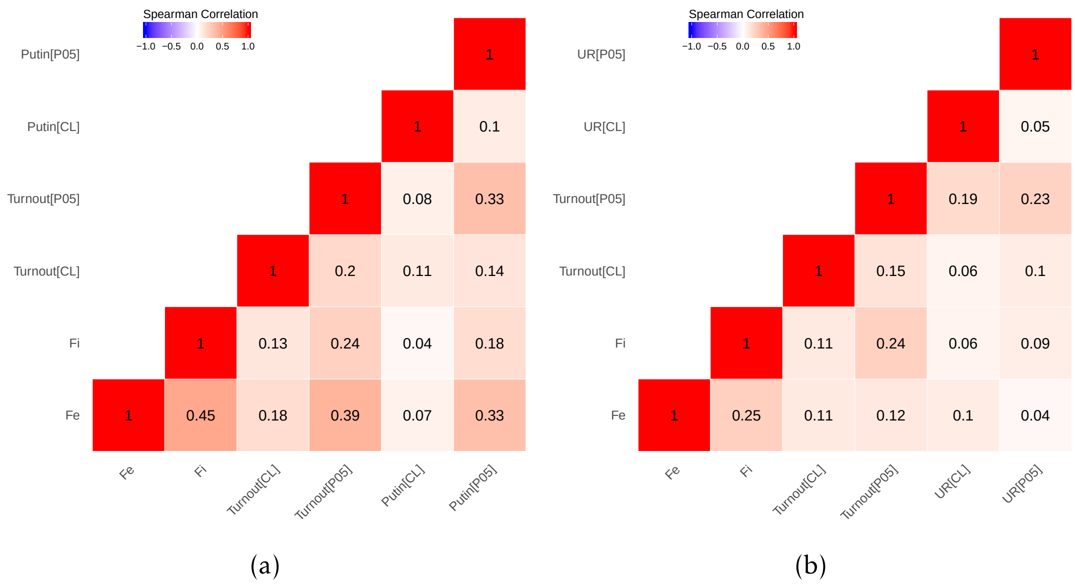
fraud f_e was still prevalent in the north of Chechnya and Dagestan Republics. Moreover, since the global mean for 2011 election is elevated compared to 2012, these results indicate the presence of less heterogeneity at higher levels of electoral anomalies. For more information on the number of territories and precincts belonging to anomalous clusters check Table A.1 in Appendix A.

Thus, taking into the account the totality of evidence, our **Hypothesis** 2 is partly confirmed by our empirical findings: the geographic clustering tests, indeed, expose the presence of election fraud clusters mainly located in the areas exhibiting poor democratic environment and the presence of the strong political machines, these are mainly the Republics and the rural territories.

Unsurprisingly, the correlation matrix built using territory-level data demonstrates somewhat weaker findings compared to the point-data correlation matrix. Notably, the correlations between the estimates of interest for the presidential elections are stronger compared to the parliamentary elections. Both finite mixture estimates weakly or moderately correlate between each other ($\rho = 0.25$ for 2011 elections; $\rho = 0.45$ for 2012 elections) and the signaling estimate [P05] ($\rho = 0.24$ for 2011 elections; $\rho = 0.39$ for 2012 elections). A moderate correlation seems to occur in 2012 between the estimates measuring signaling patterns[P05] for turnout and Putin's support ($\rho = 0.33$). I've also implemented a separate correlation analysis across the elections: its findings illustrate that the finite mixture estimates and signaling estimates, are closely correlated across both elections as well, thus, numerically indicating the consistency of election fraud quite noticeable in the maps.

Hence, the cluster analysis enables us to conclude certain data patterns are well-captured by the last-digit election forensics measures. The observed correlation between both finite mixture estimates and signaling indicators[P05] depending on the aggregation level is moderately strong. Moreover, the territory-level anomalies seem to replicate the anomalies from the precinct level quite well. This peculiar finding yields two important

Figure 2.5: Correlation Matrices for Territory-Level Data, local Moran's *I*



Notes: (a) – 2012 presidential elections; (b) – 2011 parliamentary elections.

derivations. First, with regard to the mechanism we can conclude that in selected territories election fraud definitely has been organized and coordinated not so much at the precinct-level, but rather at the higher levels of election commissions. Second, the lack of precise geographic information about polling stations, namely the absence of precincts coordinates, does not necessarily preclude us from performing cluster analysis at the territory level; the severity of election fraud at the level of polling stations is evident at the territory level as well.

Thus, empirical analysis is supportive of **Hypothesis 3** as well: depending on the electoral context, we observe moderate or strong correlations between the geographic clusters of the final mixture estimates and the geographic clusters of forensics measures associated with signaling patterns ([P05] test for turnout and incumbent), as well as anomalous last digits in vote counts[CL] found at the levels of both precincts and territories. Hence here we can conclude, that the estimates derived from the finite mixture estimator can be associated with the subnational agent's success in mobilizing his regional "political machine" to provide necessary electoral support for the Kremlin's candidate or a party.

This finding has been additionally validated by our **Hypothesis** 2.

2.7 Conclusion

Even though none of the election forensics statistics provide definitive proof of fraud, the combination of the data from observers and consideration of technological factors, along with the various election forensics measures enables us to strengthen our conjectures. This research has been specifically aimed at validating an innovative election forensics tool, i.e. the finite mixture estimator, by engaging alternative data from election observation, different voting modes and several election forensics measures sensitive to machine politics in the regions and local areas. All three hypotheses have been confirmed by my data analysis. New measures of election fraud confirm our expectations about vote rigging taking place in the polling stations with ballot boxes rather than KOIBs, and without well-trained observers rather than with them. The use of KEGs in remote areas is associated with the lack of proper election observation and elevated likelihood of electoral malfeasance – the finite mixture estimator catches this device's feature really well.

Moreover, our geographic clustering analysis exposes the presence of clusters mainly located in the areas exhibiting poor democratic climate with strong political machines – these are mainly the Republics and the rural territories.

In addition to this, based on the presented evidence, it can be also concluded that our last-digit election forensics indicators can serve as relatively good geo-predictors of the clusters of these new measures. In other words, there is a relatively strong correlation between various clusters measured with the help of different forensics indicators, which is indicative of geographic consistency between various measures of election fraud and across the Russian elections. Hence, as of now the development of a new election forensics estimator as a part of the Election Forensics Toolkit seems to be very promising, but surely, this new estimator has to be further validated across multiple electoral, political and cultural contexts. In my future research I intend to bring in more electoral data and implement validation study using several other election forensics methods. This will allow systematic comparison of election forensics methods, elucidating possible problems of validity, and thereby strengthening the election forensics research, in general.

CHAPTER III

Theory of Loyalty: Signaling Games of Election Frauds

3.1 Introduction

In recent decades authoritarian and formerly authoritarian regimes held many elections, some truly competitive and some not (Bunce & Wolchik 2011; Hyde 2011; Hyde & Marinov 2012; Levitsky & Way 2010; Wolchik & Bunce 2010). Election fraud and its detection in those states have been a concern in a large body of literature (Alvarez, Hall, & Hyde 2008; Bjornlund 2004; Cantu & Saiegh 2011; Fukumoto & Horiuchi 2011; Kalinin & Mebane 2013; Lehoucq 2003; Myagkov et al. 2009; Schedler 2006; Simpser 2013; Svolik 2012; Wintrobe 1998).

Elections are important for autocrats, because, if rightly controlled by them, elections periodically demonstrate the regime's popular support, thus reducing the likelihood of a coup by disappointed regime notables. Elections solidify the legitimacy of the autocrat among the general public (Geddes 2006; Magaloni 2006). Elections can provide lots of information that allows assessment of the strength of the potential opposition in society, even if the signal is somewhat noisy due to attempts at manipulation and fraud (Gandhi 2008, 167). Moreover, elections can also elicit information about election fraud itself: specific patterns in electoral data can persist conditional on the strategies of officials and their success in signaling the loyalty to the leader. This information is especially valuable to the autocrat, who can use the electoral data to get a snapshot of the loyalty status of the local agents, and decide on each agent's success in mobilizing his regional "political machine" to provide necessary electoral support to the leader (Gel'man 2009).

While the previous research has shown that, in Russia and elsewhere, fraud can often be readily detected (Mebane & Kalinin 2009b; Myagkov & Ordeshook 2008; Myagkov et al. 2008, 2009), it has rarely focused on the mechanisms by which election fraud can be conducted nationally. In this chapter, I argue that local agents engage in a signaling strategy, wherein election fraud signals loyalty to the leader, who distributes post-election rewards and punishments based on electoral results and turnout. This approach allows us to explain the prevalence of anomalous data patterns in turnout and voting percentage data, specifically the frequency with which a 0 or 5 appears as the last digit in a percentage. The Russian case exemplifies this phenomenon quite well: while in the mid-1990s Russian governors used strategies of bargaining, in which powerful regions provided the leader with favorable electoral outcomes in exchange for political, institutional and financial resources (Treisman 1997a, 1997b), political recentralization in the 2000s has led to revision of bargaining agreements and the imposition of electoral signaling. In the Russian case this strategy is employed by regional governors to signal their loyalty to the leader by means of fraudulently augmented electoral results and to get certain rewards in exchange, such as political survival or postelectoral transfers.

Signaling strategies and signaling games in the authoritarian setting have been the subject of previous research. For instance, Simpser (2013) focuses on a ruling party signaling its "strength" by means of increasing the winner's election margin. By creating a public impression of his own political dominance, the autocrat is able to discourage the political opposition from its quest for power (Lohmann 1994; Simpser 2013). Rundlett and Svolik (2014) claim that to overcome the limited information problem, agents start relying on the autocrat's genuine nationwide popularity as a coordination mechanism. This, however, still leads to Pareto-inferior outcome expressed in an oversupply or undersupply of fraud, resulting from a herd dynamic among agents. Kalinin (2014b) argues that the autocrat's genuine nationwide popularity can be polluted by preference falsification, which induces the agents to commit election fraud to cover up any discrepancies between polling estimates and election results. In other words, election fraud can be seen as a function of the preference falsification in the pre-electoral surveys, where the "signal of loyalty" is associated with a close match between the inflated polling estimates and incumbent's electoral returns, and *vice versa*, the "signal of disloyalty" is associated with a mismatch between both estimates.

To elucidate the institutional foundations of electoral signaling, in this chapter I introduce a game theoretic model—a signaling model (Cho & Kreps 1987)—which is used to motivate a set of empirical models that are estimated using the data from cross-national and Russian data (Kalinin & Mebane 2011). My approach utilizes the last digit of the turnout percentage and incumbent's vote percentage as the marker of fraud, reducing it to observation of 0s and 5s in the data (Beber & Scacco 2008). This approach has demonstrated its relative efficiency as a measure of fraud in our earlier works (Mebane & Kalinin 2009b).

The implications from the game-theoretic model are helpful in our understanding of the general mechanisms by which specific "signaling" markers such as 0s and 5s occur in percentages and vote counts across different political regimes. I confirm the predictions of the model via empirical analysis using data from Russia as well as cross-national data. The expansion of the "signaling game" to the cross-national realm is possible through classification of different emergent equilibria. Specifically, the presence of rigged elections and associated numerical anomalies either in democracies or autocracies can be explained by a combination of various institutional factors such as regime type (authoritarian or democratic), system of government (federal or unitary), form of government (presidential vs. parliamentary). In sum, all these factors preset a specific level of loyalty of local agents *via-a-vis* the leader, leading to the described strategic behavior expressed in signaling strategies.

The contribution of this chapter to the existing literature is threefold. First, it offers a theoretical model of electoral signaling by bringing together electoral and financial data. Second, it uses implications from formal modeling to understand the mechanisms by which the evolution of federal relations in Russia can be connected to election fraud, and explores the spread of the "signaling" phenomenon worldwide. Finally, this chapter engages two original datasets collected by the author: the Russian dataset and cross-national dataset, derived from both Adam Carr's Election Archive[1] — the largest and most comprehensive archive of electoral statistics from 182 countries, and *Government Finance Statistics(GFS)* database managed by the *International Monetary Fund*.[2]

The structure is as follows. Section 3.2 discusses the idea of signaling and loyalty in connection to election fraud, while reviewing the literature on this topic. Section 3.3 examines the basic formal model and its extension to cross-national analysis. Section 3.4 formulates basic empirical model used in the Russian and cross-national data analysis. Section 3.5 contains empirical analysis of the Russian and cross-national data. In the final part, I draw conclusions and discuss prospects for further research.

3.2 Signaling Strategies and Election Fraud

In authoritarian regimes, the leader and elites collaborate to preclude political participation by the population, making it costly for citizens to coordinate and punishing those who criticize the regime. While most citizens cannot challenge the leader, elites with key positions in the regime can still oust leaders if they can solve their coordination problem. Therefore the question becomes to what extent the leader can monitor and punish the members of elites for expressing their disapproval. In authoritarian regimes, information uncertainty about the extent of the leader's real support among the elites prevents him from effectively controlling elites (Svolik 2012; Wintrobe 1998). The solution to this

[1]http://psephos.adam-carr.net/
[2]http://elibrary-data.imf.org/

dilemma becomes possible on the one hand through control of the intelligence organs, allowing the Leader to monitor and punish the disloyal members, and on the other hand, through the use of positive incentives to encourage the elites to insure loyalty and compliance. For instance, Bueno de Mesquita and colleagues suggest that this is precisely why leaders of authoritarian regimes create small winning coalitions: the exchange between loyalty and private goods available with small winning coalitions strengthens ties between the leader and the elites (de Mesquita, Smith, Siverson, & Morrow 2004; Gehlbach 2013).

The distribution of rents in exchange for loyalty is undermined by the principal-agent problem between the autocrat and his local agents, where the agents are willing to engage in fraud only in situations where vested risks are compensated by certain financial awards, such as rents and payments coming from the principal (Rundlett & Svolik 2014). This observation is supported by the general theory of agency, arguing that the principal benefits from giving the agent some rent to induce him to take a desired but unobservable action and to truthfully reveal his private information. This exchange, however, is costly in terms of the policymaker's objective and decreases economic efficiency of the outcome compared to non-authoritarian states (Dixit 2010).

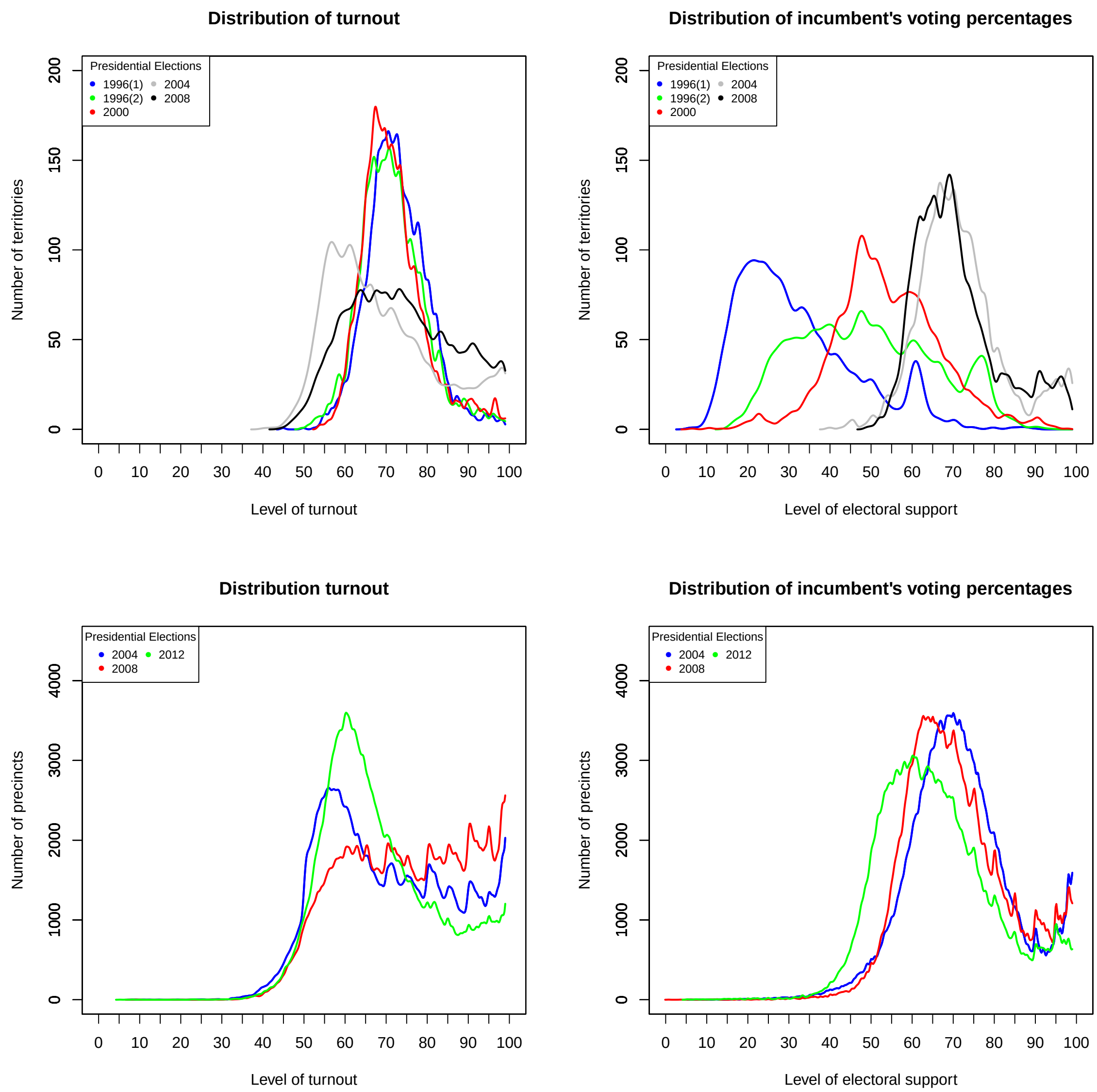
Even though the repression of various information channels helps an autocrat to efficiently deter any risks associated with the emergence of possible challengers (de Mesquita et al. 2004; Egorov, Guriev, & Sonin 2009; Wintrobe 1998), elections can still provide a wealth of useful information. Although manipulation and fraud may make the signal somewhat noisy, elections allow assessment of the strength of the potential opposition in a given society (Gandhi 2008, 167). The limited information problem, however, with regard to the leader's genuine popularity makes it quite difficult for him and the local agents to efficiently allocate election frauds throughout the system, as well as to differentiate the costly signals of agent's loyalty expressed in election frauds. In spite of this, some parts of the "signaling" information or the fingerprints of electoral fraud are well embedded in the electoral data and can be easily detected by a loyalty-seeking autocrat or by anomaly-seeking election forensics researchers. In fact, those agents with highest risks of exclusion from the winning coalition are most likely to radiate stronger signaling patterns (de Mesquita et al. 2004; Gehlbach 2013). In this sense elections serve an important purpose to the autocrats. If rightly controlled in their hands, elections periodically demonstrate the regime's popular support, thus reducing the likelihood of a coup by disappointed regime notables, and solidifying the legitimacy of the autocrat among the general public (Geddes 2006; Magaloni 2006). Also, electoral information enables the leader to get a snapshot of the loyalty status of the local agents and their success in mobilizing their regional "political machines" to provide necessary electoral support to the leader (Gel'man 2009).

Signaling patterns serve as the markers of election fraud within the data, and can be detected using various kinds of the digit-based tests. For instance, the last-digit vote counts test (Beber & Scacco 2008) argues that if the turnout or vote counts reflected the natural complex of processes that cause people to vote or not to vote, we would expect the counts' last digits to be uniformly distributed (i.e., each digit zero through nine would occur equally often). The rational strategic patterns of election fraud can be detected by the second-digit test: we might expect that if substantial vote switching or ballot stuffing is occurring, we should see significant departures from the Benford's expected mean for the second digit ($\bar{j}_B = 4.187$) (Mebane 2010; Mebane & Kalinin 2009a). The patterns in the data resulted from the use of signaling strategies are best explored by the "last digit of percentages" of turnout or voting percentages, which is a special case of the Beber and Scacco (2008) approach. According to Kalinin and Mebane (2013) the signaling strategies are explicitly present when the expected value for the mean of this indicator variable is significantly higher $E(P05s) = 0.2$.

In fact, the notion of signaling strategies has been especially acute during the Soviet period. During this time, governors would use "false accounting" (*pripiski*), designed to affect the measures of the level of regional output and help them to avoid punishment (Harrison 2009). Because of this "false accounting", it comes as no surprise that with the start of new Russian recentralization in 2000s, such Soviet practices were restored in relation to Russian contemporary elections. As a result, the presence of electoral fraud became a basic signaling mechanism of regional bosses' loyalty and of their ability to control administrative resources to the Kremlin's benefit. Electoral signaling can be readily detected by analyzing the percentages of electoral outcomes. If electoral signaling occurs, electoral "pripiski" are most likely to take place with rounded percentages of turnout or vote percentages, which is the easiest and most readily detected way to report basic information to superiors. In such cases, favorable percentages are first sent down from the Kremlin to the regional elections commissions, which passes this information further down to the territory-level commissions and, finally, precincts (Kalinin & Mebane 2013).

One of the obvious ways to detect signaling patterns is to display kernel density estimates for precinct-level incumbent's vote shares and turnout for the Russian presidential elections. For most of the years, the figures in Figure 3.1 show the presence of non-normal distributions, exhibiting spikes at locations corresponding to the excess of vote shares and turnout values at values of 60%, 65%, 70%, 75%, 80%, 85% and 90% (Buzin & Lubarev 2008; Mebane & Kalinin 2009a, 2009b). The authors argue that the only acceptable explanation for the spiked distributions is a wide-spread adjustment of those figures to specific "rounded" figures. Inspecting the last digits of the original precinct-level turnout counts adds to the impression that many of them are faked. If the turnout counts reflected the natural complex of processes that cause people to vote or not to vote, we would expect the counts' last digits to be uniformly distributed, i.e. each digit zero through nine would occur equally often (Beber & Scacco 2008). Table C.1 in Appendix C shows for each digit the signed square root of the discrepancy between the observed frequency of the digit and the frequency of 0.1 expected if the distribution is uniform. The distribution of the last digits in the actual turnout counts from 2003-2012 is very

Figure 3.1: Turnout and Vote Support Across Precincts



often far from uniform for both presidential and parliamentary elections.

A value of 2.0 or greater in magnitude represents a significant discrepancy. The table shows that across all Russian elections there are always too many zeros and fives, with one exception too few nines.

The rise in political centralization leads to integration of local agents into the superstructure of the center with economic and political resources flowing from the leader to subnational units. From the cross-national perspective, the unitary system of government, in which the center delegates authority to subnational units, making subnational units more dependant on its political and economic resources, should be prone to signaling strategies. Moreover, in the federal system of government without gubernatorial election, i.e. de facto unitary systems, such as Russia's, one would expect the presence of similar signaling patterns. The signaling game is built around the political loyalty, defined as the local agent's ability to control the political, social and economic spheres in the dependent region so as to provide the leader with the favorable electoral outcomes. In return for electoral outcomes, agents can be rewarded with financial inflows or appointments, or, in the event of a negative outcome, punished by the leader. Even when the political regime is stable and durable, the actual benefits from committing election frauds could far outweigh the actual costs, inducing the local agents to adopt their signaling strategies on a regular basis (Rundlett & Svolik 2014). The federal systems of government can be characterized by signaling strategies of subnational agents in the same way as the unitary. For instance, Filippov, Ordeshook, and Shvetsova (2004) observe in a federal system, regional executives' "aggressive programs of improving their units' position" may extend to elections: "If, for instance, the enforcement of antifraud election provisions is weak or nonexistent, and if regional chief executives can influence voting or the tabulation of votes for national as well as regional offices, then those executives possess a powerful asset that can be used to short-circuit constitutional provisions written to direct federal bargaining elsewhere" (Filippov et al. 2004, 119).

This chapter argues that the pattern of fraudulent electoral results can be explained by the presence of signaling games between the regions and the Leader/Center. Fraudulent electoral results show how favorable electoral results can be delivered by the regional elites to display their loyalty to the Leader/Center in exchange for administrative and financial rewards.

3.3 A Formal Model

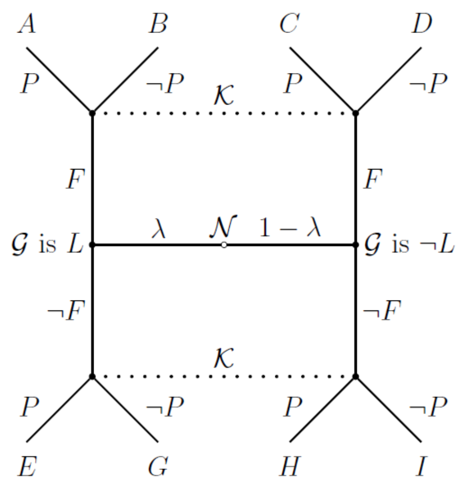
Consider the signaling game (Cho & Kreps 1987) represented by the diagram in Figure. 3.2[3] $\mathcal{N}$ denotes a random move by Nature to produce a first player (the local agent or the governor, $\mathcal{G}$) who is either loyal (L) or not ($\neg L$). Then Prob(L) = λ and Prob($\neg L$) = $1-\lambda$. In the election the governor then either commits fraud (F) or not ($\neg F$). Player 2 (the Leader, $\mathcal{K}$) does not know whether $\mathcal{G}$ is loyal, but $\mathcal{K}$ does observe $\mathcal{G}$'s move. $\mathcal{K}$ then either punishes (P) or not ($\neg P$). The payoffs are given at the bottom of Figure 3.2. The interpretation of the symbols used in the payoff definitions is as follows.

- $w \geq 0$ is the value of electoral punishment by voters for fraud committed in the election; $w > 0$ — the value of electoral punishment when elections take place, and $w = 0$ — the value of electoral punishment when elections are absent.
- $p > 0$ is the value of punishment imposed by $\mathcal{K}$
- $v > 0$ is the value of excess votes produced by fraud
- $t > 0$ is the value of transfers from $\mathcal{K}$ to $\mathcal{G}$
- b is a coefficient that when multiplied by t gives the present discounted value of the future expected to be produced by a transfer; this may be positive or negative
- $d > 0$ is the value to $\mathcal{K}$ of replacing a disloyal $\mathcal{G}$

Given equivalent actions by $\mathcal{K}$, fraud is always worse for $\mathcal{G}$ due to the sanction from voters. That is, if $\mathcal{G}$ is loyal and $\mathcal{K}$ always punishes, then playing F gives $\mathcal{G}$ a payoff of $-w-p$ while playing $\neg F$ gives $-p$. If there is no sanction from voters, $w = 0$, then F and $\neg F$ give $\mathcal{G}$ the same payoff given an identical response from $\mathcal{K}$. The payoffs to $\mathcal{G}$ from F are always w subtracted from the corresponding payoff from $\neg F$.

[3] A more detailed description of the formal model can be found in Kalinin and Mebane (2013)

Figure 3.2: Game Diagram



symbol	$\mathcal{G}$	$\mathcal{C}$
A	$-w-p$	$v-p$
B	$-w+t$	$(b-1)t+v$
C	$-w-p$	$v-p+d$
D	$-w+(b+1)t$	$v-t$
E	$-p$	$-p$
G	t	$(b-1)t$
H	$-p$	$-p+d$
I	$(b+1)t$	$-t$

If fraud happens, $\mathcal{K}$ always gains excess votes v. If $\mathcal{K}$ doesn't punish, then $\mathcal{G}$ always gains a transfer from $\mathcal{K}$, t, which costs $-t$ to $\mathcal{K}$. If $\mathcal{K}$ punishes, then $\mathcal{G}$ always loses $-p$ which also costs $-p$ to $\mathcal{K}$. But if a disloyal $\mathcal{G}$ is punished (e.g., fired), then $\mathcal{K}$ gains d.

One key difference between a loyal $\mathcal{G}$ and a disloyal one is who retains any future surplus generated by a transfer from $\mathcal{K}$. Compare the payoffs when a loyal $\mathcal{G}$ commits fraud and is not punished to the payoffs when a disloyal $\mathcal{G}$ commits fraud and is not punished: the difference is that the term bt is added to $\mathcal{K}$'s payoff in the former case but is added to $\mathcal{G}$'s payoff in the latter case. A similar situation holds when $\mathcal{G}$ does not commit fraud and is not punished: the disloyal $\mathcal{G}$ retains the surplus while with a loyal $\mathcal{G}$ $\mathcal{K}$ retains the surplus.

The game is presented in multiagent normal form (Myerson 1991). The strategies of the loyal $\mathcal{G}$ are now denoted F_1 and $\neg F_1$ while the disloyal $\mathcal{G}$'s strategies are F_2 and $\neg F_2$. $\mathcal{K}$'s strategies are now P_1 and $\neg P_1$ if acting after fraud and are P_2 and $\neg P_2$ if acting after no fraud. The multiagent strategic normal form of the game appears in Table B.1 of Appendix B. The necessary conditions for a perfect Nash equilibrium are tested for the set of possible pure strategy equilibria. The strategy profiles along with the payoffs that go to $\mathcal{G}$ and $\mathcal{K}$ are listed in Table B.2 of Appendix B. The strategy profiles, the results of testing whether the profile can be a Nash equilibrium and a brief description of the requirements for the profile to be an equilibrium appear in Table B.3 of Appendix B. The tests are done by comparing payoffs produced with each profile to the payoffs produced with the profiles produced by changing each agent's strategy while holding the other strategies constant.

According to the signaling model, four parameters are central to our understanding of why specific equilibria hold and why, in particular, the "electoral signaling" equilibrium arises. These parameters are d, the value to the Leader of replacing a disloyal governor, λ, the probability that a governor is loyal, which is presumably increased by having the governor be appointed instead of elected, b, the future returns expected to be produced by a transfer, and w, the value of electoral punishment by voters for fraud committed in the election. Here loyalty is regarded as a choice each governor makes and not an immutable personality trait, $\lambda \in (0,1)$: $\lambda = 0$ indicates no chance of loyal governor at all, and $\lambda = 1$, a high chance of loyalty.

Several profiles that can be equilibria have conditions that require either $\lambda = 0$ or $\lambda = 1$ (See Table B.3 in Appendix B). These are the profiles labeled I*, II*, V*, VI*, XI* and

XVI*.[4]

While some of these equilibria have potentially interesting features, the condition $\lambda = 0$—no chance of loyalty at all—is too extreme. Once elections are abolished or all governors are appointed, the circumstance of $\mathcal{K}$ being certain of $\mathcal{G}$'s loyalty ($\lambda = 1$) becomes at least thinkable, but first we will consider equilibria that admit uncertainty: $\lambda \in (0,1)$. The profiles that can be equilibria and admit uncertainty about $\mathcal{G}$'s loyalty are the ones labeled III*, IX*, XII* and XV*.[5]

The signaling theory implies that over all the country, regions are diverse, so a single configuration of the parameter values of the game model does not characterize the whole country.[6] The future returns expected from a transfer, b, may be positive or negative. Negative b values are associated with corruption and political opportunism: as far as the Leader is concerned, economic resources transferred to a corrupt region are expected to produce no significant value in the future, and if the resources facilitate regions' gaining further autonomy and even independence, the return on transfers to a region may even be evaluated as strictly negative. Alternatively, b may be positive. Indeed, if b is like a normal investment, we should have $b \geq 1$: the transfer is at least expected to pay for itself. Different regions may at any one time have different values of b. For instance, during the 1990s, the threat of regions leaving the Russian Federation was very real, so b was negative. For this period, the game model does not explain the relationship that may exist between election fraud and postelection transfers as well, but when the model is applied it suggests that when $b < 0$, the relationship between election fraud and transfers is such that governors who commit fraud are likely worse off than governors who do not.

In the case of greater centralization, the clearest change is that the value of d becomes

[4] Explicitly, these profiles are I*, $(F_1, F_2, \neg P_1, \neg P_2)$; II*, $(F_1, \neg F_2, \neg P_1, P_2)$; V*, $(F_1, \neg F_2, P_1, \neg P_2)$; VI*, $(F_1, \neg F_2, \neg P_1, \neg P_2)$; XI*, $(\neg F_1, F_2, \neg P_1, P_2)$ and XVI*, $(\neg F_1, F_2, \neg P_1, \neg P_2)$.

[5] Explicitly, these profiles are III*, $(F_1, F_2, \neg P_1, P_2)$; IX*, (F_1, F_2, P_1, P_2); XII*, $(\neg F_1, \neg F_2, \neg P_1, P_2)$ and XV*, $(\neg F_1, \neg F_2, P_1, \neg P_2)$.

[6] Note that we have modeled the relationship between the Leader and one governor. It is assumed that the Leader plays such a game independently in each region, and that regional actors learn nothing from one another's experience. Reality undoubtedly involves more interaction between regions than this, but it is intractable to extend the game to one in which the Leader simultaneously interacts with all other regions.

high and increasing over time. The increase in d reflects how local "political machines" were coopted into the power vertical. As long as the loyalty of governors is not certain—$0 < \lambda < 1$—and $b < 0$, there may be an alternation between III*, in which both types of governors commit fraud, and XV*, in which neither type of governors commits fraud—an alternation that is related to transfers and punishments and depends on loyalty. As a result, this will induce an association between transfers and punishments, on the one hand, and election fraud, on the other. With regards to Russia, for instance, recentralization greatly reduced separatist concerns, so that perhaps $b > 0$. A positive value of b would rule out XV* as an equilibrium. Recentralization likely raised the typical value of λ, so that b may more often exceed the lower bound. In the period before gubernatorial elections were abolished—in particular 2004—this may imply an alternation between III* and XII*. Now a payoff of $-w + t[1 + b(1 - \lambda)]$ to the governor who commits fraud, under III*, is likely positive, while the payoff to a governor who does not commit fraud, under XII*, is $-p < 0$.

Once regional elections take place or all governors are appointed, as in Russia in 2008, $w = 0$ rules out XII*. If $b > 0$ and having governors be appointed means that often $\lambda = 1$, then VI*, or $(F_1, \neg F_2, \neg P_1, \neg P_2)$, comes into play as a possible equilibrium alternative to III*, with the alternation between the two depending on the balance between transfers and punishments. If transfers are high enough, VI* may come into play so that only truly loyal governors commit fraud. The occurrence of both III* and VI* would complicate assessing the relationship between transfers, punishments and fraud, because in III* governors commit fraud and are not punished while in VI* governors commit fraud and are punished. Nonetheless, III* and VI* give identical payoffs if $\lambda = 1$. If often $b < 0$ notwithstanding recentralization, then II* can explain why high λ goes with fraud and higher transfers, and low λ goes with no fraud and lower transfers, if the value of b is associated with λ.

To summarize, for Russia in the 1990s the game model does not explain the relationship that may exist between election fraud and postelection transfers very well. In the 2000s the clearest change is that the value of d becomes high and increasing over time: recentralization signals such a change, and the abolition of gubernatorial elections in 2004 decisively indicates it. The increase in d reflects how local "political machines" were coopted into the power vertical. This will induce an association between transfers and punishments, on the one hand, and election fraud, on the other.

Hypothesis 1: *In Russia of the 90s, elements of bargaining prevent the observation of signaling model, whereas in 2000, fraud-signal-transfers-reward regime seems to be fully in place.*

The signaling model can be extended to the cross-national setting as well. This game is characterized by multiple equilibria, which can be successfully mapped using the parameters from equilibria conditions, onto different typologies of political regimes (autocracy vs. democracy), political systems (federal system vs. unitary system), the presence or absence of regional elections. Table 3.1[7] presents all the equilibria profiles with conditions containing both *institutional loyalty* λ, being a function of political regime, political system, and electoral punishment w denoting the presence of regional elections. The table depicts the results of matching regime type with the system of government. Intuitively the magnitude of λ has been divided into three broad categories with high, medium and low values of λ. Depending on the degree of the *institutional loyalty* and the presence of electoral punishment of the governors *ceteris paribus*, the probability of electoral signaling with voter fraud and subsequent rewards/punishments is expected to differ. The table shows that in highly centralized authoritarian regimes with the absence of possibility of electoral punishment on behalf of the voters, i.e. with high levels of *institutional loyalty* λ, the local agents will be more prone to signaling strategies directed to the Leader by means of fraudulently augmented turnout or inflated voting support for the ruling party/candidate.

[7]The Table is built based on the Table B.3 in Appendix B. Only those equilibria were selected in which w, and λ are defined, except $(\neg F_1, \neg F_2, \neg P_1, P_2)$.
$\lambda = f(Regime, System, w)$.
$(\mathrm{F}_1, F_2, \neg P_1, P_2)$ equilibrium is defined for $\lambda \in [0, 1]$.

For the purpose of my analysis, only those equilibria have been classified which contain both the value of λ, reflecting the local agent's loyalty at the country-level, and w, entailing the presence or the absence of the regional elections with which the electoral punishment for the voter fraud takes place.

High level of loyalty ($\lambda = 1$) corresponds to hard authoritarian regimes. According to the Table 3.1, the federal system of government in those regimes implies modest levels of electoral punishment with only loyal type of the governor committing fraud; in contrast, the unitary system of government with absent elections of the regional heads suggests two separate equilibria outcomes: the one in which both types of the governors commit fraud, and the one in which only the loyal type commits fraud (it holds when the amount of transfers exceed the amount of punishment and the future cash flows are positive). As far as the Leader's punishment is concerned, both types of local agents tend to be punished for their actions in the case of the federal system of government. One of the feasible reasons for this is that those regional heads who are engaged in committing election fraud are likely to be ousted by the voters at the regional elections. This incentivizes the Leader to outpace the unhappy voters and financially punish such a governor after the signaling has been spotted. In contrast, in the unitary systems of government election fraud is never punished by the Leader.

A similar logic of mapping equilibria outcomes has been applied to soft authoritarian regimes, where the value of λ is found in the range between 0 and 1. Table 3.1 demonstrates that within the federal regimes, election fraud is never conducted by any of the agents and none of them is punished for the rigged election outcomes. In contrast, the model predicts that in soft authoritarian regimes with the unitary system of government ($w = 0$) always experience election fraud which is strategically exercised by both types of the agents, but the Leader's punishment strategy is quite ambiguous. The observation of both types of local agents tending to resort to election fraud, can be understood from

Table 3.1: Matching Regime Type and System of Government

Regime type and system of government	Institutional loyalty	Electoral punishment (by voters), w	Equilibrium	Conditions	Frauds	Punishment (by Leader)
Hard authoritarian regime, federal system of government	High λ	Yes	$(F_1, \neg F_2, P_1, \neg P_2)$	$\lambda = 1 \cap b \leq 0 \cap (1-b)t \geq p \geq t \cap 2p \geq w$	Loyal commits fraud	Fraud punished
Hard authoritarian regime, unitary system of government		No	$(F_1, F_2, \neg P_1, \neg P_2)$	$\lambda = 1 \cap w = 0$	Both commit fraud	Fraud unpunished
		No	$(F_1, \neg F_2, \neg P_1, \neg P_2)$	$\lambda = 1 \cap w = 0 \cap t \geq p \cap b \geq 0$	Loyal commits fraud	Fraud unpunished
Soft authoritarian regime, federal system of government	Medium λ	Yes	$(\neg F_1, \neg F_2, P_1, \neg P_2)$	$\frac{t+p}{w+t+p} \leq \lambda < 1 \cap \frac{-(p+t)}{(1-\lambda)t} \geq b \geq \frac{v+t-p}{t}$	No fraud	Fraud punished
Soft authoritarian regime, unitary system of government		No	$(F_1, F_2, \neg P_1, P_2)$	Complicated	Both commit fraud	Fraud unpunished
		No	(F_1, F_2, P_1, P_2)	$\lambda < 1 \cap w = 0 \cap \frac{-(p+t)}{(1-\lambda)t} \geq b$	Both commit fraud	Fraud punished
Democratic regime, federal system of government	Low λ	Yes	$(\neg F_1, \neg F_2, \neg P_1, P_2)$	$w \geq p + t \cap t + d \geq p + v$, loyalty is undefined	No fraud	Fraud unpunished
Democratic regime, unitary system of government		No	$(\neg F_1, F_2, \neg P_1, P_2)$	$\lambda = 0 \cap w = 0 \cap b \geq \frac{w-p-t}{t}$	Non-loyal commits fraud	Fraud unpunished
		No	$(\neg F_1, F_2, \neg P_1, \neg P_2)$	$\lambda = 0 \cap w = 0 \cap b \geq 0 \cap p \geq d + t$	Non-loyal commits fraud	Fraud unpunished

costless signaling ($w = 0$) , inducing the nonloyal type of local agents to imitate its loyalty towards the Leader. Hence,

Hypothesis 2: *In autocracies one would observe electoral signaling in both the federal and the unitary systems of government higher than in democracies.*

The democratic regime is characterized with a low level of institutional loyalty to the Leader ($\lambda = 0$) for the unitary system of government, and undefined λ for the federal system of government. In the case of the federal system of government, none of the agents commits actual election fraud and none of them is punished, the situation in the unitary states is much more sophisticated. $(\neg F_1, \neg F_2, \neg P_1, P_2)$ is the only equilibrium with undefined λ. This equilibrium fits democracies with the federal system of government quite well. In the unitary system of government election fraud conducted by nonloyal agent, only happens in the situation, where $w = 0$. Moreover, the nonloyal agent can always avoid punishment for conducting election fraud. The same is true for the loyal agent who never commits election fraud and is never punished. Hence,

Hypothesis 3: *In democracies one would observe greater electoral signaling in the case of the federal system of government, suggesting the presence of subnational authoritarianism, and only nonloyal type of the local agent committing fraud in the unitary system.*

The efficiency of signaling in determining the agents' loyalty status by the Leader is one of the most important implications of the equilibria analysis. It is determined by the type of the equilibria outcome, facilitating the Leader's ability to learn about agent's type: in a pooling equilibrium with two different types choosing the same message and in a separating equilibrium different types selecting different messages. In the hard authoritarian regimes both systems of federal government imply separating equilibria, making it easier for the Leader to learn about the agent's type, with the loyal type always resorting to election fraud and nonloyal type always abstaining from it. Conversely in a soft authoritarian regime with the unitary system of government both types will commit election fraud, making it impossible for the Leader to disentangle them. The latter situation, resulting in the Leader being unable to determine if the present discounted value of the future expected to be produced by a transfer would belong to him or to the nonloyal agents. If we turn our attention to equilibria profiles of the soft authoritarian regimes, we would find the constellation of pooling equilibria, in which the nonloyal type of the agent fully imitates the strategic behavior of the loyal types. In the case of the federal system of government none of the agent types implements election fraud, fearing retaliation from the voters, whereas in the unitary system of government both types do.[8] In contrast to conventional wisdom, the observation of multiple pooling equilibria with widely spread imitational strategies of nonloyal agents would be in place under the soft authoritarianism. Finally, democratic regimes are characterized by one pooling equilibria, in which none of the types conducts election fraud (federal system of government), and two separating equilibria with the loyal type abstaining from election fraud and nonloyal type conducting it (unitary system of government).

The equilibrium analysis across multiple regime types provides us with an important insight on the sources of election fraud: in the hard authoritarian regime we would predict mostly loyal types of local agents conducting election fraud and getting away with it. In the soft authoritarian regimes both types act more synchronically in delivering fraudulent results with the ambiguous punishment patterns. Finally, in democratic regimes loyal types never conduct election fraud, but nonloyal types of the governors do, which partially undermines the notion that the opposition is interested in playing by democratic rules (Przeworski 1991).

3.4 Basic Empirical Model and Its Variants

To interpret the empirical model, transfers t are not defined by the totality of actual transfers from the Leader to regional governments, but rather as a deviation from the

[8]Of course, the local agent in order to avoid punishment by the electorate, can attempt to falsify the regional elections as well. However, my basic assumption implies that in the federal states the regime will be hosting free and fair elections $w = 1$.

plain relationship between successive years' transfers. That is, if the regression of total transfers T in region i in the year immediately following the election, s, on the level of transfers in the year preceding the election, $s-$, is written $T_{it} = c_0 + c_1 T_{it-} + u_{it}$, for disturbance u_{it} and coefficients c_0 and c_1, then the amount of transfers subject to manipulation may be represented by a term t_{it} in the form

$$T_{it} = b_0 + b_1 T_{it-} + t_{it} + e_{it}. \tag{3.1}$$

The coefficients c_1 and b_1 should be close to 1.0, capturing the relative stability of the social and economic needs and resources that affect the total amount of transfers going to an area, t_{it} can be thought as a short-run distortion. In particular t_{it} exists in the year following a presidential election. The game model motivates a special form for t_{it} that is discussed further below. The point to make now is that for the game model's b to be interpreted in terms of the future returns associated with the component t_{it} of T_{it} and not with the entirety of T_{it}.

My empirical data analysis is divided into two parts: (1) the analysis of authoritarian regime, such as Russia, and (2) cross-national analysis using the aggregated electoral results.

3.4.1 Empirical Model for Russia

The empirical model is motivated by the associations suggested by the game model, focusing on the form of the short-run distortion term t_{it}. The empirical model does not follow in any direct way from the game model, but rather picks up on its core idea that the signaling structure induces a short-run distortion in transfer payments that depends on election fraud and loyalty. I analyze data measuring T_{it}, transfer payments to region i for postelection year s: T_{it} measures the amount of transfers per 10,000 people allocated to the region. T_{it} is a function of preelection transfer payments (T_{it-}) and other variables in models of the form

$$T_{it} = b_0 + \mathbf{z}'_{it}\mathbf{c} + \lambda_i + \mathbf{f}'_{it}\mathbf{d} + \lambda_{it}\mathbf{f}'_{it}\mathbf{g} + e_{it}{}^9, \tag{3.2}$$

where b_0 is a constant term and $\mathbf{c}$ and $\mathbf{d}$ are vectors of coefficients, $\mathbf{z}_{it}$ is a vector of covariates, $\mathbf{f}_{it}$ is a vector of fraud measures, λ_i is a function to be defined that represents the probability the governor is loyal and e_{it} is a normally distributed disturbance. $\mathbf{z}_{it}$ contains variables that plausibly affect the level of transfer payments from Leader to each region. The term $\lambda_{it}\mathbf{f}'_{it}\mathbf{g}$ corresponds to the idea expressed by t_{it} in (3.1), for particular fraud measures $\mathbf{f}_{it}$ and particular functional forms for λ_{it}: postelection transfer payments are a function of readily observable fraud signals, depending on the probability of loyalty. For some years (1996, 2000) there is territory-level election data. For other years (2004, 2008) I have both territory- and precinct-level (UIK-level) election data.

To measure election fraud, I use Frauds Indices, defined as follows. First compute voter turnout and incumbent's percentage in the presidential election for each precinct or territory as a percentage rounded to the nearest digit. Define two variables `turnoutlast0` and `incumbentlast0` that is equal to 1 if the last digit of turnout and incumbent's variable is a zero and equal to 0 for other digits, and define another pair of variables `turnoutlast5` and `incumbentlast5` that is equal to 1 if the last digit is a five and equal to 0 for other digits. The variables $\texttt{Turnout}_{fraud}\texttt{f}_0$ and $\texttt{Incumbent}_{fraud}\texttt{f}_0$ are the means of `turnoutlast0` and `incumbentlast0` for each region, and $\texttt{Turnout}_{fraud}\texttt{f}_5$, $\texttt{Incumbent}_{fraud}\texttt{f}_5$ are the means of `turnoutlast5` and `incumbentlast5`. The Frauds Indices are $\texttt{fraudT0}_{it}, \texttt{fraudI0}_{it}, \texttt{fraudT5}_{it}, \texttt{fraudI5}_{it}$.

Vector $\mathbf{z}_{it}$ contains other variables that may relate to transfer payments: $\texttt{Republics}_{it}$ is a dummy variable measuring whether a region belongs to a Republic[10]; $\texttt{Incumbent}_{it}$ is the percent of the incumbent party's electoral support in the region (in 1996 the incumbent

[9]Because of the convergence issues T_{it-} enters the model only as a part of λ_i component, which is a substantial departure from the original model.

[10]Republics are Russian regions with predominantly the non-Russian ethnicity.

is Yeltsin, in 2000 and 2004 it is Putin, and in 2008 it is Medvedev); and $\texttt{turnout}_{it}$ is the turnout percentage defined above.

The term λ_{it} represents a notion of loyalty slightly different from that in the game model. The game has the governor moving before Leader, with Nature first selecting the type of the governor. In reality the governor makes a decision whether to be loyal, in response to anticipations of what Leader will do and in light of preelection conditions. Among those conditions are preelection actions by the Leader. A simple way to connect preelection actions to the game model is to imagine that they influence the value of λ: preelection actions affect the likelihood that the governor is loyal. Here the λ_{it} is defined as a logistic function of preelection transfers (T_{it-} or $\texttt{Transfers}_{it}$) and possibly several other preelection variables: $\texttt{Appointed}_{it}$, a dummy variable measuring whether the governor was appointed a year before the elections; $\texttt{Bilateral}_{it}$, a dummy variable measuring whether the regions signed a bilateral treaty by the year of elections; and $\texttt{GovernorUR}_{it}$, a dummy variable measuring whether a governor openly supported Unity/United Russia after 1999 parliamentary elections. The formulation is

$$\lambda_{it} = \frac{1}{1 + \exp(-a_0 - \mathbf{x}'_{it}\mathbf{a})} \tag{3.3}$$

where a_0 is a constant, $\mathbf{x}_{it}$ is a vector containing $\texttt{Transfers}_{it}$ and possibly some of the other preelection covariates, and $\mathbf{a}$ is a vector of coefficients. Variables $\texttt{Appointed}_{it}$ and $\texttt{GovernorUR}_{it}$ measure actions affecting or taken by the governor that would suggest the governor is loyal, and $\texttt{Bilateral}_{it}$ indicates disloyalty. Higher preelection transfers may indicate either the presence or purchase of loyalty (Hyde & O'Mahony 2010).

The rationale behind selection of the nonlinear functional form is explained by estimation of loyalty. Since we are dealing with probabilities of loyalty, we need to have a function that naturally varies between 0 and 1. Moreover, logistic function has a good theoretical underpinning. Both lower and higher levels of loyalty are associated with the weaker effect of loyalty on dependent variable (election fraud or transfers), which can be especially the case if the Leader is indifferent between too small or too large levels of loyalty.

The model (3.2) represents a very simple implementation of a mixture model. Fraud measures and transfers are related when the governor is loyal and not otherwise. The probability that the governor is loyal is measured by λ_{it}. All parameters are assumed to be identical for the various types of governors, so the interaction term involving λ_{it} is sufficient to represent the mixture. Conceptually, the fraud variables play a role only when the governor is loyal. Regression relationships based on linear predictors are not specifically implied by suggested theoretical model, but they represent the easiest way to get at possible relationships, taking into account the likelihood that multiple, correlated and conceptually distinct variables are associated with the occurrence of fraud.

The theoretical model supports different predictions about the relationships among fraud, transfers and other variables in different time periods. The game model suggests that transfers will be negatively associated with measures of fraud, where loyalty is relatively high, during the 1990s. During the 2000s, once the Kremlin commences recentralization and Putin comes to power, and particularly after 2004 when gubernatorial elections are abolished, the game model predicts that when loyalty is high the incidence of fraud will be positively associated with transfers.

To guide the choice of what to include in $\mathbf{x}_{it}$, I include the vector of variables that relate directly to the probability that the governor is loyal: substantive judgments about what factors matter. This principle draws on the judgment that different institutional arrangements existed at different times, so that actions to incentivize or reflect loyalty are different at different times. It is always assumed that $\mathbf{x}_{it}$ includes $\mathtt{Transfers}_{it}$, preelection transfers. The $\mathtt{Appointed}_{it}$ variable enters the equation in 1996 and 2008, because when these three elections occurred, some governors were appointed while others were elected.[11] Variable $\mathtt{GovernorUR}_{it}$, used in years 2000, 2004 and 2008 to indicate whether

[11] The 2004 presidential election held on March 14, 2004, before gubernatorial elections were abolished at the end of 2004.

the governor was nominated on the United Russia ballot in the previous parliamentary elections (1999, 2003 and 2007), measures how closely affiliated a governor is to the party of power Unity/United Russia and the governor's predisposition to use necessary economic and administrative resources of the region to support the Kremlin's candidate at the presidential elections. Variable $\texttt{bilateral}_{it}$, used in years 1996, 2000 and 2004 to indicate whether the region has signed a bilateral treaty with the Leader, measures the political autonomy of the governor from the Leader.[12] Because most bilateral treaties were abolished after 2004, $\texttt{bilateral}_{it}$ is excluded in 2008.

3.4.2 Empirical Model for Cross-National Analysis

For the purpose of cross-national analysis I resort to nonlinear least squares model specifications with postelectoral transfers serving as a response variable. The proposed mixture model implies that the future short-run distortions in the levels of financial centralization result from the interaction effects between the election fraud measures and the *institutional loyalty* λ_{it}, which also encompasses the measure of financial centralization in a given electoral year. Here I propose a slightly revised variant of the model estimated for the Russian case, and adopted it to cross-national analysis:

$$T_{it} = b_0 + \mathbf{z}'_{it}\mathbf{c} + \mathbf{y}'_{it}\mathbf{t} + \lambda_{it} + \lambda_{it}\mathbf{f}'_{it}\mathbf{d} + e_{it}{}^{13}, \tag{3.4}$$

where b_0 is a coefficient and $\mathbf{c}$ and $\mathbf{d}$ are vectors of coefficients, $\mathbf{z}_{it}$ is a vector of covariates, $\mathbf{y}_{it}$ is a vector of time covariates, $\mathbf{f}_{it}$ is a vector of fraud measures, λ_{it} is a function to be defined that represents the probability of institutional loyalty. In this case loyalty is represented by λ_{it}, which can be defined as a logistic function of key institutional variables: $\texttt{Appointed}_{it}$ — a dummy variable denoting whether the regional executives

[12] In Russia bilateral treaties have been negotiated between the Center and forty-seven regions during the 90s. These assumed the provision of additional economic resources in exchange of political support for the Kremlin's policies.

[13] Because of convergence issues T_{it-} enters the model only as a λ_i component, which is a substantial departure from the original model.

are appointed by the central authorities or not; $\texttt{Polity}_{it}$ —an interval variable defining regime's level of democracy; $\texttt{Presidential}_{it}$ — a dummy variable specifying the form of government (presidential vs. parliamentary); $\texttt{Federal}_{it}$ — a dummy variable denoting the system of government (federal vs. unitary). I also added two additional controls: $\texttt{Rallies}_{it}$, which is a total sum of three components: strikes, rallies and demonstrations from the "Cross-National Time-Series Data Archive" and lagged annual GDP growth rate taken from the World Bank data ($\texttt{GDPgrowth}_{it}$). The vector $\mathbf{z}_{it}$ contains variables that plausibly affect the level of transfer payments to subnational units. The term $\lambda_{it}\mathbf{f}'_{it}\mathbf{d}$ corresponds to the idea expressed by t_{it} in model (3.1), for particular fraud measures $\mathbf{f}_{it}$ and particular functional forms for λ_{it}: postelection transfer payments are a function of readily observable fraud signals, depending on the probability of loyalty.

All the nonlinear least squares models for the Russian and cross-national data were estimated using `nls2()` function in **R**.

3.5 Empirical Data Analysis

The data used in this research were taken from multiple sources. The data on financial transfers for different periods were kindly provided by Daniel Treisman and Andrei Starodubtsev. The data on governor's affiliation with United Russia in 2003 and 2008 were kindly given by Olesya Tkacheva. The electoral data for 1996 and 2000 presidential elections were provided by Alexei Sidorenko. The data for 1996 and 2000 include only territory-level election reports. The electoral data for 2004 and 2008 were obtained from the website of Russian Central Elections Commission (`http://www.cikrf.ru`). The data for 2004 and 2008 include both precinct-level (UIK-level) and territory-level election reports. Other data were collected by the author from the databases of Federal State Statistics Service and the websites of regional administrations. The cross-national electoral data on comes from Adam Carr's Election Archive. An additional measure of election fraud capturing the extra-constitutional irregularities was been drawn from the Database of Political Institutions. The financial data on fiscal decentralization was been taken from the *Government Finance Statistics(GFS)* database managed by the *International Monetary Fund*.

3.5.1 Empirical Analysis of the Russian Case

Electoral signaling can be readily detected by analyzing the percentages of electoral outcomes. If electoral signaling occurs, electoral manipulations with figures are most likely to take place with rounded percentages of turnout or incumbent's vote percentages, which is the easiest and most readily detected way to report basic information to superiors. In such case, favorable percentages are first sent down from Kremlin to the regional elections commissions, which pass this information further down to the territory-level commissions and, finally, precincts. Of course there is no direct evidence that this "passing down" is the precise procedure used to commit the fraud I allege exist, nor is reliable information available about exactly how the fraud is implemented. Ballot box stuffing and simply writing down false numbers are likely mechanisms (e.g. Boldyrev 2012), but also likely is fraud using phony voter registrations (Arbatskaya 2004) or perhaps other methods (Lehoucq 2003). Since the territory-level commissions serve as an intermediate body between regional and precinct level commissions, I suppose that these have the highest leverage to produce faked numbers in the system and report them to the upper level in percentages. Thus I expect numeric anomalies with percentages to be detected at both tiers of the system, i.e. at both precinct and territory levels.

The results from the multivariate regression analysis are presented in Tables 3.2 and 3.3. Since the sample size used in this analysis is small and there is no substantive justification for which outliers should be excluded, I keep all of the observations in multivariate regression analysis and account for any possible outliers by reporting White's robust standard errors. To estimate the model (3.3) here I apply to nonlinear least squares using transfer payments, T_{it}, measured in postelection years 1997, 2001, 2005 and 2009.[14] Each model is estimated for each year separately. Moreover, two different indicators of transfers designed to check robustness of my findings are included as dependent variables: transfers per capita and the proportion of transfers in the regional revenues. For 1996 the model is estimated separately for the first and the second round elections using fraud measures derived respectively from each election (see models M(01) and M(02) in Table 3.2[15]). In 1996 λ_i is a function of several loyalty indicators including $\mathtt{Transfers}_{it}$, $\mathtt{Bilateral}_{it}$, and $\mathtt{Appointed}_{it}$, where only $\mathtt{Transfers}_{it}$ yields statistically significant positive coefficient for $\hat{a}_1$ in the first model. My initial expectation that none of the coefficient estimates $\hat{f}_0$ and $\hat{f}_5$ of the Frauds Index yield statistically significant results for the 90s is supported by the findings: only the effect of anomalies in incumbent's vote shares $\hat{f}_5$ is positive and significantly different from zero. In both rounds of elections fraud, as measured by the Frauds Index measures, seems to play only limited role in signaling, while preelection transfers show statistically significant effects on postelection transfers.

The model M(03) in Table 3.2 reports results for 2000. As one would expect, the coefficient estimate $\hat{a}_1$ for $\mathtt{Transfers}_{it}$ in λ_{it} is significantly positive. Besides, the coefficient estimates for Putin's vote percentages $\hat{f}_0$ and $\hat{f}_5$ and for anomalies in turnout $\hat{f}_5$ are also characterized by positive and statistically significant effects. This finding bears the evidence about election forensics measures being indicative of the relatively larger signaling phenomena taking place in 2000 compared to 1996.

Models M(04) and M(05) report the results for 2004 based on territory-level and precinct-level election returns. Again, the coefficient estimates for pre-electoral $\mathtt{Transfers}_{it}$ yield a positive statistically significant effect. $\mathtt{GovernorUR}_{it}$ in both models yield negative effects that are statistically significant at $\alpha = 0.1$. While the original intuition suggests

[14] For estimation we use the `nls()` function of **R** (R Development Core Team 2011).

[15] $\mathtt{Transfers}_{it} = b_0 + c_1\mathtt{Republics}_{it} + c_2\mathtt{Incumbent}_{it} + c_3\mathtt{Turnout}_{it} + f_0\mathtt{fraudT0}_{it} + f_5\mathtt{fraudT5}_{it} + f_0\mathtt{fraudI0}_{it} + f_5\mathtt{fraudI5}_{it} + \lambda_{it} + \lambda_{it}\cdot(f_0\mathtt{fraudT0}_{it} + f_5\mathtt{fraudT5}_{it} + f_0\mathtt{fraudI0}_{it} + f_5\mathtt{fraudI5}_{it}) + e_{it}$,

$$\lambda_{it} = \frac{1}{1+\exp\{-(a_0 + a_1\mathtt{Transfers}_{it-} + a_2\mathtt{Bilateral}_{it} + a_3\mathtt{GovernorUR}_{it} + a_4\mathtt{Appointed}_{it})\}}.$$

Table 3.2: Postelectoral Model: Effect of Election Fraud on Logged Transfers Per Capita

	M(01)	M(02)	M(03)	M(04)	M(05)	M(06)	M(07)
Constant b_0	-1.68	-0.812	-0.758	0.189	0.297	-3.367***	3.637***
	(1.802)	(1.278)	(1.008)	(0.761)	(0.657)	(0.287)	(0.331)
Republics c_1	0.085	0.185	0.277	0.084	0.13		0.045
	(0.225)	(0.215)	(0.194)	(0.207)	(0.148)		(0.066)
Incumbent c_2	-0.507	0.082	0.428	1.264	-0.353	1.53*	-0.993
	(0.875)	(0.662)	(0.879)	(1.021)	(0.867)	(0.618)	(0.659)
Turnout c_3	-0.451	-1.467	1.44	0.928	0.303	0.304	0.156
	(2.438)	(1.674)	(1.557)	(0.793)	(0.649)	(0.552)	(0.502)
Constant a_0	6.131*	12.328*	1.967*	-7.995***	-5.118***	-1.68	-11.477***
	(2.985)	(6.586)	(0.951)	(2.029)	(1.315)	(5.919)	(2.308)
Transfers a_1	3.967*	8.454	2.969***	3.025***	1.717***	-2.848	2.861***
	(1.975)	(4.518)	(0.923)	(0.756)	(0.419)	(2.232)	(0.596)
Bilateral a_2	0.294	0.5	-0.476				
	(0.775)	(1.229)	(0.572)				
GovernorUR a_3			0.527	-1.492*	-0.444	0.612*	-0.533*
			(0.53)	(0.59)	(0.252)	(0.239)	(0.235)
Appointed a_4	0.036	1.015				-0.215*	-0.413
	(0.606)	(0.956)				(0.086)	(0.222)
fraudT0 f_0	1.592	0.28	-0.135	2.408***	1.41**	0.77**	2.02***
	(0.867)	(0.986)	(0.711)	(0.653)	(0.519)	(0.281)	(0.559)
fraudT5 f_5	0.142	-0.713	2.492*	0.202	6.19***	1.114***	4.671*
	(0.845)	(0.827)	(1.053)	(0.642)	(1.985)	(0.302)	(1.9)
fraudI0 f_0	1.019	-0.145	0.747***	1.576*	4.049	0.044	0.39
	(0.907)	(0.737)	(0.215)	(0.624)	(2.096)	(0.293)	(1.205)
fraudI5 f_5	1.063	1.643*	1.821*	0.656	3.193	-0.243	-0.27
	(0.799)	(0.765)	(0.84)	(0.613)	(2.205)	(0.273)	(1.443)
$\hat{\sigma}$	0.753	0.723	0.631	0.514	0.421	0.341	0.259
N	81	80	79	82	80	77	78

Notes: Robust standard errors in parentheses. Significance levels: *p $\leq$ 0.05, **p $\leq$ 0.01, ***p $\leq$ 0.001. Listed models: M(01) – regression model for 1996 (first round); M(02) – regression model for 1996 (second round); M(03) – regression model for 2000; M(04)-M(05) – regression models for 2004 territory and precinct-level elections; M(06)-M(07) – regression models for 2008 territory and precinct-level elections.

that the governors aligned with the party of power are expected to be recipients of larger transfers, the coefficient's negative sign is indicative of the leader's parsimonious policies with regard to the governors affiliated with United Russia. In both models built for 2004, the presence of statistically significant positive coefficient estimates $\hat{f}_0$ and $\hat{f}_5$ for anomalies in turnout and Putin's vote percentages at $\alpha = 0.05$ and $\alpha = 0.1$ levels, respectively, demonstrate the presence of a strong relationship between anomalies and transfers as predicted by the theory. Specifically, when the probability of loyalty is high, readily observable fraud is associated with higher levels of postelection transfers directed to each region. This is a kind of result the game model suggests should happen when either game model parameter b is positive and there is alternation between the equilibria, as described by III* and XII*, or when b is negative and there is alternation between fraud and no fraud, as allowed by II* when there is suitable association between b and λ. Notably, the figures for incumbent's vote share ($\hat{c}_2$) and the turnout proportion itself ($\hat{c}_3$) are not significantly associated with transfers for either levels of analysis. The fact that λ_i is a function of different covariates when territory-level versus precinct-level returns are considered may reflect the reality that different kinds of officials are involved in fraud committed in the respective election commissions. Perhaps, in reality, election fraud in Russia in 2004 involved multiple levels of signaling, not merely signaling between each governor and the Leader.

Both models M(06) and M(07) in Table 3.2 show the results for 2008 for both territory-level and precinct-level election returns. For both levels of electoral data aggregation, the coefficient estimates $\texttt{Transfers}_{it}$ are positive and significantly different from zero. If precinct-level model demonstrates that loyalty expressed in United Russia's affiliation and appointments can be associated with lower transfers, the territory-level model provides us with the opposite finding: party affiliation with the United Russia can be related to higher amounts of transfers. Interestingly, the coefficient estimates $\hat{f}_0$ and $\hat{f}_5$

Table 3.3: Postelectoral Model: Effect of Election Fraud on the Log Share of Transfers in the Regional Revenues

	M(01)	M(02)	M(03)	M(04)	M(05)	M(06)	M(07)
Constant	-0.052	-0.338	-3.37***	-1.905***	-3.227*	-2.11***	-2.203***
	(0.557)	(0.496)	(0.787)	(0.246)	(1.287)	(0.4)	(0.397)
Republics c_1	0.091	0.127*	0.297	0.171	0.078	0.229*	0.235*
	(0.057)	(0.059)	(0.159)	(0.094)	(0.07)	(0.091)	(0.089)
Incumbent c_2	-0.504	-0.172	-0.597	0.152	0.283	1.082	0.157
	(0.402)	(0.146)	(0.797)	(0.355)	(0.408)	(0.718)	(0.775)
Turnout c_3	-0.533	-0.237	2.02	0.215	0.023	-0.917	-0.546
	(0.607)	(0.613)	(1.396)	(0.247)	(0.311)	(0.559)	(0.486)
Constant a_0	1.148*	1.055***	8.829*	3.72***	3.041***	4.827***	4.013***
	(0.523)	(0.317)	(4.06)	(1.107)	(0.738)	(1.137)	(1.094)
Transfers a_1	1.845***	1.656***	4.052*	3.907***	2.559***	3.112***	2.473***
	(0.337)	(0.276)	(1.92)	(0.582)	(0.536)	(0.623)	(0.669)
Bilateral a_2	-0.297	-0.455					
	(0.429)	(0.302)					
GovernorUR a_3			0.368	-0.747*	-0.097	0.321	0.142
			(0.824)	(0.327)	(0.127)	(0.381)	(0.201)
Appointed a_4	-0.336	-0.325				0.232	0.011
	(0.33)	(0.254)				(0.416)	(0.234)
fraudT0 f_0	-0.177	0.638*	1.004*	0.095	0.186	0.694*	0.327
	(0.399)	(0.276)	(0.505)	(0.222)	(0.322)	(0.293)	(0.218)
fraudT5 f_5	-0.155	0.025	1.25*	0.577	3.129	0.758**	2.329*
	(0.602)	(0.294)	(0.534)	(0.361)	(2.186)	(0.271)	(0.964)
fraudI0 f_0	0.35	-0.781	-0.272	1.057***	3.181	0.157	1.695*
	(0.282)	(0.538)	(0.315)	(0.311)	(2.317)	(0.316)	(0.838)
fraudI5 f_0	0.059	0.072	0.659	-0.212	2.328	-0.02	0.057
	(0.221)	(0.188)	(0.535)	(0.29)	(1.499)	(0.215)	(1.434)
$\hat{\sigma}$	0.204	0.184	0.626	0.368	0.324	0.285	0.276
N	81	81	80	82	82	79	79

Notes: Robust standard errors in parentheses. Significance levels: *p $\leq$ 0.05, **p $\leq$ 0.01, ***p $\leq$ 0.001. Listed models: M(01) – regression model for 1996 (first round); M(02) – regression model for 1996 (second round); M(03) – regression model for 2000; M(04)-M(05) – regression models for 2004 territory and precinct-level elections; M(06)-M(07) – regression models for 2008 territory and precinct-level elections.

for turnout measured at the precinct-level data model are significantly positive and substantively comparable in the magnitude to the values estimated for 2004. Thus, when the probability of loyalty is high, readily observable fraud with turnout committed at the precinct level is associated with higher levels of postelection transfers directed to the regions. Overall, the demonstrated models yield broad variation of signaling strategies throughout the studied period: relatively weak signaling patterns in the 90s; relatively strong signaling is associated with turnout and vote shares in the 2000 elections; strong signaling is associated with turnout and weak signaling associated with incumbent's support in 2004; finally, very strong signaling is associated with turnout and the absence of any signaling whatsoever with regards to Medvedev's vote percentages back in 2008.

Table 3.3[16] exhibits a different set of models designed to check the robustness of my previous findings by using the proportion of transfers in the regional revenues as a dependent variable. In general, the results are compatible with my previous findings from Table 3.2: signaling patterns seem to persist across all the years. The coefficient estimate $\mathtt{Transfers}_{it}$ $\hat{a}_1$ is significantly positive across all my models. The signaling patterns are prevalent for the second round of 1996 where $\hat{f}_0$ shows its statistical significance, and also 2000 elections with both anomaly measures for turnout being statistically significant. It is worth mentioning that while the credibility of my findings for the 1990s can be undermined by the issues of data quality, especially for the shares of transfers in the regional revenues, the models M(04)-M(07) built for 2004 and 2008 are more trustworthy. If in 2004, the territory-level models show the presence of apparent signaling patterns in incumbent's percentages $\hat{f}_0$, in 2008 precinct-level models yield quite comparable levels of signaling positively associated with postelectoral transfers. Unlike the 2004 models though, both 2008 models display signaling patterns associated with turnout in both precinct and territory levels. Thus, alternative measure of transfers provides us with a

[16] $\mathtt{Transfers}_{it} = b_0 + c_1\mathtt{Republics}_{it} + c_2\mathtt{Incumbent}_{it} + c_3\mathtt{Turnout}_{it} + f_0\mathtt{fraudT0}_{it} + f_5\mathtt{fraudT5}_{it} + f_0\mathtt{fraudI0}_{it} + f_5\mathtt{fraudI5}_{it} + \lambda_{it} + \lambda_{it}\cdot(f_0\mathtt{fraudT0}_{it} + f_5\mathtt{fraudT5}_{it} + f_0\mathtt{fraudI0}_{it} + f_5\mathtt{fraudI5}_{it}) + e_{it}$,
$$\lambda_{it} = \frac{1}{1+\exp\{-(a_0 + a_1\mathtt{Transfers}_{it-} + a_2\mathtt{Bilateral}_{it} + a_3\mathtt{GovernorUR}_{it} + a_4\mathtt{Appointed}_{it})\}}$$

solid empirical proof of the signaling concept: anomalies associated with election fraud are closely related to transfers per capita as well as the share of transfers in the regional revenues.

Table 3.4: Panel Data Analysis with the First-Difference Estimator, OLS

	M(01)	M(02)	M(03)	M(04)	M(05)	M(06)
Incumbent	13.972***	-1.347***	11.331**	-0.476	-131.145*	-0.524*
	(2.841)	(0.13)	(4.186)	(0.543)	(51.428)	(0.229)
Turnout	-6.979	-4.827***	13.518	-6.73***	70.383	0.692***
	(14.686)	(1.037)	(17.552)	(1.551)	(44.38)	(0.121)
Transfers	6.877***	0.058	7.613***	0.031	2.043	-0.023
	(1.438)	(0.147)	(1.524)	(0.224)	(0.133)	(0.111)
fraudT0	-5.297	-0.208	-16.946	1.234*	-103.029	0.129
	(6.079)	(0.339)	(9.591)	(0.533)	(88.227)	(0.19)
fraudT5	-2.888	-0.454	2.089	0.014	130.244*	0.05
	(6.378)	(0.358)	(5.985)	(0.563)	(49.825)	(0.172)
fraudI0	6.052	-0.022	-4.805	-0.283	42.783	0.015
	(5.354)	(0.159)	(10.362)	(0.21)	(50.237)	(0.178)
fraudI5	3.816	-0.17	18.824*	0.888	69.677	0.114
	(10.706)	(0.36)	(8.909)	(0.554)	(46.776)	(0.172)
Transfers × $fraudT0$	-15.109*	-0.099	0.023	-4.416**	-0.382	2.422**
	(6.908)	(1.206)	(18.67)	(1.775)	(2.497)	(0.733)
Transfers × $fraudT5$	4.477	-0.89	-21.725*	-1.453	-5.27***	1.165
	(10.564)	(0.847)	(9.49)	(1.857)	(1.641)	(0.834)
Transfers × $fraudI0$	-4.577*	2.266	-0.637	-0.838	3.006*	0.212
	(1.961)	(1.173)	(3.536)	(1.411)	(1.442)	(1.712)
Transfers × $fraudI5$	2.538	3.582**	-38.701**	-1.692	-3.685*	3.042***
	(8.813)	(1.212)	(14.596)	(2.532)	(1.572)	(0.758)
$\hat{\sigma}$	5.219	0.289	5.872	0.404	27.062	0.113
N	80	80	80	80	80	80

Notes: Robust standard errors in parentheses. Significance levels: *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$. Listed OLS models: a) the first-difference estimator for 1996(first round) and 2000 with transfers per capita M(01) and M(02) with the share of central transfers in the regional budget as dependent variables; b) the first-difference estimator for 1996(second round) and 2000 with transfers per capita M(03) and share of central transfers in the regional budget M(04) as dependent variables; c) the first-difference estimator for 2004 and 2008 with transfers per capita M(05) and the share of central transfers in the regional budget M(06) as dependent variables.

Next, for additional robustness check I perform panel data analysis, which enables me to estimate both temporal effects of election fraud associated with loyalty in the 1990s and 2000s, and also addresses the problem of region-specific heterogeneity that can potentially bias my estimates of interest. In particular, I obtain two separate territory-level datasets for 1996-2000 and 2004-2008, and then I compute the first-difference estimators using the ordinary least squares regression, which is an unfortunate departure from the original nonlinear model. Since data for the 1990s and 2000s come from different data sources, to avoid the measurement error, I exclude first-difference estimator between 2000 and 2004. The proposed linear model includes direct and indirect effects of election fraud, enabling me to estimate the conditional effects of anomalies on postelectoral transfers. Moreover, in order to insure comparability of results across different elections I resort to curtailing the "loyalty" component by reducing it to only one variable — pre-electoral $\texttt{Transfers}_{it}$. My findings from the panel data analysis are shown in Table 3.4[17]. According to the Table, while in the 90s incumbent's vote share is positively related to transfers per capita, in the 2000s the sign of this effect has been reversed to a negative. One of the most feasible explanations of this counterintuitive finding originate from the difference between electoral contexts and varying mobilization mechanisms of the regional "political machines," used to provide necessary electoral support to the national ruling elites. The 1996-2000s period was more crucial for regime's own stability, as these were years of transition, as compared to 2004-2008, which was a period of consolidation. In addition, the Table also provides us with the limited evidence that $\texttt{Turnout}_{it}$ coefficient yields its negative effect on the proportion of transfers in the regional revenues in the 90s, while in 2000s its effect is positive, thus displaying regime's greater attention to the level of turnout in the 2000s rather than in the 90s.

Since the inclusion of interaction effects between pre-electoral transfers and anomalies associated with turnout and incumbent's support makes their interpretation quite complicated, here I build graphs depicting the marginal effects of electoral anomalies on

[17]Ordinary least squares estimates for all the models were used. $\Delta\texttt{Transfers}_{it} = b_0 + b_1\Delta\texttt{Incumbent}_{it} + b_2\Delta\texttt{Turnout}_{it} + b_3\Delta\texttt{Transfers}_{it-} + b_4\Delta\texttt{fraudT0}_{it} + b_5\Delta\texttt{fraudT5}_{it} + b_6\Delta\texttt{fraudI0}_{it} + b_7\Delta\texttt{fraudI5}_{it} + b_8\Delta\texttt{Transfers}_{it-} \times \Delta\texttt{fraudT0}_{it} + b_9\Delta\texttt{Transfers}_{it-} \times \Delta\texttt{fraudT5}_{it} + b_{10}\Delta\texttt{Transfers}_{it-} \times \Delta\texttt{fraudI0}_{it} + b_{11}\Delta\texttt{Transfers}_{it-} \times \Delta\texttt{fraudI5}_{it}$.

transfers. All figures are sorted in such a way as to simplify the comparative analysis between the 1990s and 2000s. According to Figure C.1(a) in Appendix C, while for the 1990s, as pre-electoral transfers increase, the marginal effect of election fraud $\hat{f}_0$ on post-electoral transfers decreases. In the 2000s, however, the marginal effect of election fraud $\hat{f}_0$ on post-electoral transfers takes the opposite sign. The remaining pairs of figures agree with each other in terms of direction of the marginal effects: the graph for $\hat{f}_5$ yields a negative statistically significant linear trend for 1996-2000(c) and 2004-2008(d), and yields a positive statistically significant effect for 1996-2000(e) and 2004-2008(f). In a similar vein, Figure C.2 in Appendix C depicts the marginal effect of anomalies associated with turnout on post-electoral $\texttt{Transfers}_{it}$: while in the 90s the increase in preelectoral transfers contributed to noticeable drop in the marginal effect of turnout's fraud $\hat{f}_0$ on post-electoral transfers, in the 2000s the observed effect is statistically significant and positive (See Figure C.2(a,b) in Appendix C). Finally, the marginal effects of $\hat{f}_5$ on postelectoral transfers are negative for both studied periods (See Figure C.2 (c,d) in Appendix C).

In sum, while the 2000s have a number of instances in which the marginal effects are negative, thus contradicting my theoretical expectations, this period is also characterized by mainly positive marginal effects, while the 1990s are characterized by mainly negative ones. Interestingly, the drastic differences between both periods has been well-observed for $\hat{f}_0$ in incumbent's percentages and turnout. While in the 1990s $\hat{f}_0$ would result in the drastic decline in the amount of transfers directed from the Leader, in the 2000s this association has been reversed: the presence of excessive 0s has been always compensated with additional postelectoral transfers. Thus, the presented modified panel data analysis is in agreement with my by-year regression analysis, supporting theoretical implications from the model.[18]

The results from estimating model (3.3) using data from the various elections strongly

[18] In addition to OLS analysis, after computing first differences for the data I also apply to nonlinear least squares estimation (See Table C.2). Although key model parameters such $\texttt{Incumbent}_{it}$, $\texttt{Turnout}_{it}$ and $\texttt{Transfers}_{it}$ demonstrate almost similar in sign statistically significant coefficients, the change in specification has led disappearance of statistically significant positive signs of coefficient estimates for anomalies.

confirm the theoretical argument that refers to the game model and also validates using the fraud measures that focus on particular digits occurring in turnout figures. Thus, my **Hypothesis 1** has been confirmed. All examined Russian presidential elections show evidence of fraud that is described more or less well by the game model. For elections from 2000 on, and very clearly for the elections of 2004 and 2008, evidence indicates that there was widespread fraud motivated by governors' desire to signal their individual loyalties to the Center. The fact that signaling in 2004 is apparent in both territory-level and precinct-level turnout data suggests, of course, that many officials besides merely the governors are involved in the fraud. The signaling in 2008 is apparently connected to postelection turnout rewards at the precinct-level. These both observations say something about election fraud activities having become even more completely federalized in ways that go beyond the scope of our game model. Likely hierarchies of signals are involved.

The specific institutional change that began as Putin came to power in 2000 severely impacted the structure incentives of local agents. In terms of the game model, the value of the parameter d greatly increased. As recentralizaton gained hold, the threat associated with transfers to regions often decreased—the threat of regional secession disappeared—so that the long-run returns associated with transfers likely often increased: b was less often negative or at least often less negative. These changes led to revision of the strategies governors and the Kremlin found optimal, leading to the situations seen in 2004 and 2008, where election frauds are easy to detect because governors are using them to send signals to the Kremlin. Of course, the methods used by Myagkov et al. (2009) that focus on turnout also diagnose fraud in all of these Russian elections, but their methods do not focus specifically on turnout and vote figures' last digits. As it has been shown, in Russia, the occurrence of zeros or fives in the last digit is connected to an extensive signaling structure wherein election frauds are closely interlinked with postelection rewards and punishments.

Overall, our theoretical propositions are supported by my data. The results sometimes display a complex picture. The presidential election of 1996 seems to contain elements of bargaining that the signaling model is not optimally designed to represent. In the first round of the 1996 election we see empirical results that match what the game model suggests should happen—governors who commit election fraud are worse off. The presidential election of 2000 reflects political uncertainty and institutions under transition: governors who signal by committing fraud seem to be rewarded in an incipient way. By 2004 and continuing into 2008, the fraud-signal-transfers-reward regime seems to be fully in place. The rewards in terms of postelection transfers from committing fraud in order to signal seem to be comparable in 2004 and 2008.

The prevalent "signaling" mechanism raises a fundamental problem for the political regime: regional elites after being coopted by the Center are inclined to exploit the existing asymmetry in distribution of information between the Center and themselves for their own benefit, by systematically distorting information in their best interests, including electoral information. Is it "folly" to rest "the stability of a federation on the shoulders of some electoral scheme" (Filippov et al. 2004, 175)? B. D. Taylor (2011) suggests perhaps yes. The scope of this analysis is too narrow to support an evaluation of whether what Bednar (2009) calls the "safeguards" of federalism have been improved or worsened by the highlighted changes. But in Russia, the signals of political loyalty, in exchange for reduced interference by the Center highlighted here occur in the context of great informational asymmetry between the regions and the Center. The true level of support for the ruling party is difficult to discern. Both III* and XII*, which, among the equilibria, best describe what happens in 2004 and 2008, are pooling equilibria: both loyal and disloyal governors take the same actions. This makes the Center unable to separate the types of the heads of the regions—who is really supportive of the regime and who is not but is successfully faking their support.

3.5.2 Cross-National Data Analysis

The data on electoral anomalies comes from Adam Carr's Election Archive, which is one of the largest and most comprehensive archive of electoral statistics from 182 countries.[19] All the country-year data from 1997 to 2010 available at the subnational level in different formats has been extracted and processed to derive several measures of interest: the last digit of the percentage and the last digit of vote counts for the candidate or party who has received the most popular votes, as well as the last digit of the total vote counts and turnout. Additionally, the auxiliary data, containing the last digit in the percentage and in the last digit in vote counts across all the candidates, has been utilized. As a result, I have an electoral data sample that includes 567 country-year observations. An additional measure of election fraud, capturing the extra-constitutional irregularities reported by international observers or mentioned in the text of the sources, also has been used from the Database of Political Institutions. The only potential drawback of this measure, which needs to be accounted for, is that there may have been instances of fraud/violence that were not reported, thus resulting in false negatives. Since application of alternative better indicators, such as Judith Kelley's data on electoral observation, has been limited due to a poor overlap with my electoral data, I have decided to remove it from my the present analysis. For a similar reason, the empirical measure of loyalty norm based on the the CNTS dataset has been eliminated from my analysis (de Mesquita et al. 2004).

Unfortunately, the data scarcity on the regional grants and transfers at the *Government Finance Statistics(GFS)* database managed by the *International Monetary Fund* prevented me from using these most appropriate indicators. As a substitute for the relevant dependent variable, in this chapter I apply to two measures of fiscal decentralization rigorously described in Dziobek, Mangas, and Kufa (2011), both of which supposedly must be sensitive to any inflows and outflows in the regional revenues. These two financial decentral-

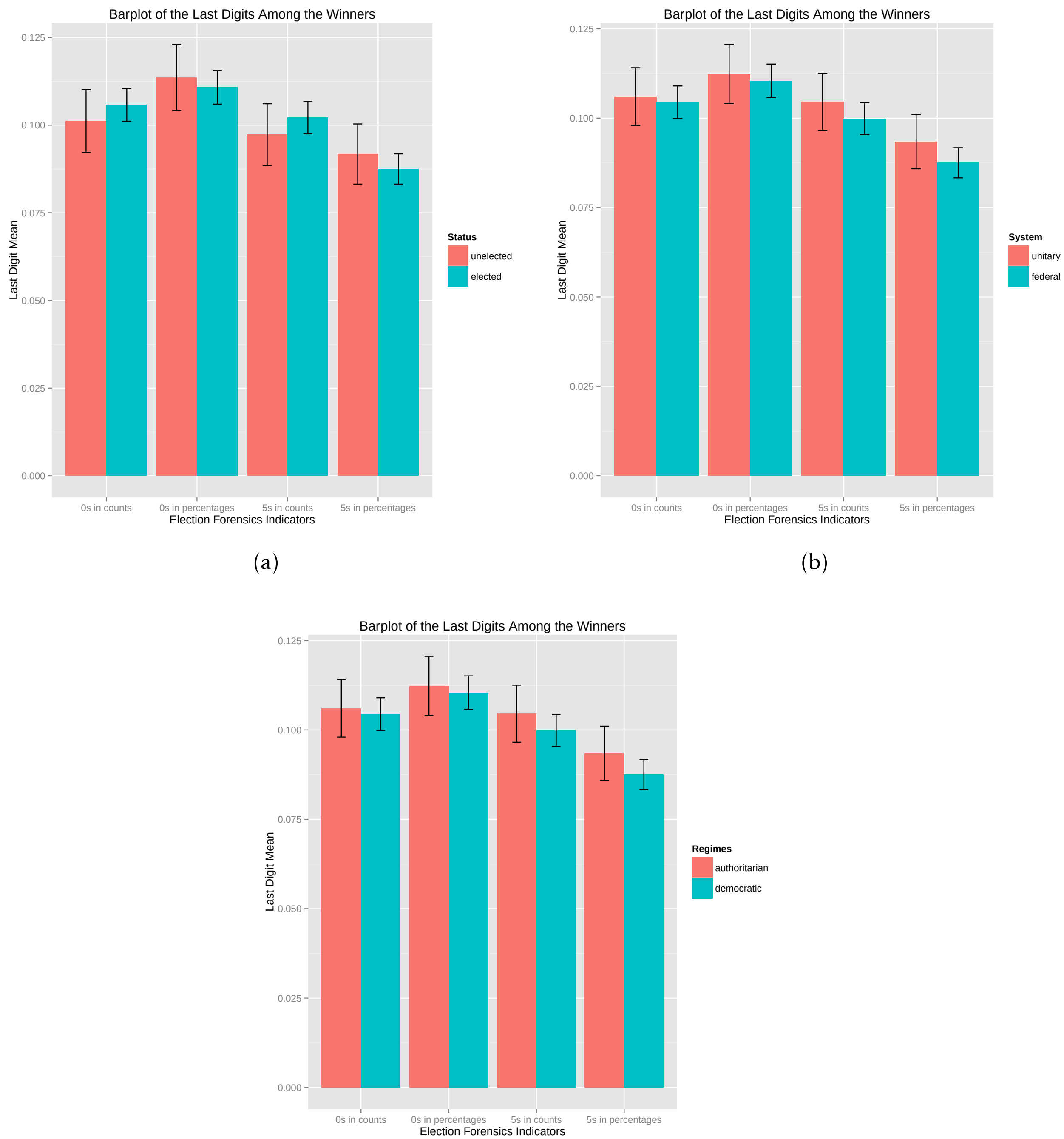
[19] http://psephos.adam-carr.net/

ization indicators picked for the purpose of my analysis are *revenues* and *tax effort*. The financial decentralization involving the *revenues* is computed as a $GL2/GL3$ ratio, i.e. the ratio between the noncash revenues of the central government and the noncash revenues of the general government both measured as a percentage of GDP.[20] The alternative measure is the *tax effort*, which is the fiscal indicator defined as the sum of tax revenue and compulsory social security contributions also computed as a $GL2/GL3$ ratio. According to the manual, the notion of "tax burden" actually duplicates the notion of "fiscal burden", which is understood as the "amount of compulsory transfers by units of the general government sector on the rest of the economy", which can be approximated by the sum of tax revenue and social security contributions ("The IMF Statistics Department's Government Finance Statistics Manual 2001" 2001, 48). Both measures reflect the simple notion, by which the increase in the values of indicators is tied to the increase in the level of financial centralization. As a result of merging financial centralization data with my electoral data, the size of the original data sample has dropped to 375 country-year observations. I also use two additional control variables: collective action and economic development. The collective action variable implies opposition's capability to mobilize support against election fraud. Economic development can be regarded as a factor affecting the Leader's financial redistribution policies (Treisman 2011); as well as the demand for allocation of additional resources by the local agents.

The set of institutional covariates comprising *institutional loyalty* are obtained from the Database of Political Institutions coming from the World Bank. The included measures are as follows: political system (parliamentary or presidential), presence of regional elections (in other words, whether the regional government are directly/indirectly elected or appointed). A measure of federalism has been obtained from Daniel Treisman's dataset

[20] According to "The IMF Statistics Department's Government Finance Statistics Manual 2001" (2001, 13-15), "[t]he political authority of a country's central government extends over the entire territory of the country. The central government can impose taxes on all resident institutional units and on nonresident units engaged in economic activities within the country" and "The total economy of a country consists of the set of all resident institutional units, and the general government sector consists of all resident general government units".

Figure 3.3: Barplots for the Winners



(a) (b) (c)

assembled for this chapter (Treisman 2000). A measure reflecting the country-year level of democracy has been taken from the Polity IV project.

My cross-national analysis starts with the construction of the barplots with 90% confidence intervals for the winners, all the participants on the ballot, and total vote counts and turnout. It is worth noting that before starting my analysis all the percentages for parties and candidates less than 1% were removed from my data. Figure 3.3(a) illustrates the differences in 0s and 5s in the winners' electoral results between the countries with appointed and elected regional authorities: these anomalies in the percentages are characterized by a well-expected small excess for the states with unelected local agents over the elected ones, however, this difference is not statistically significant. Figure 3.3(b) depicting the comparison between the states with unitary and federal systems, shows excess of 0s and 5s in the unitary states over the federal. Unfortunately, overlapping confidence intervals between the box-plots prevent us from making any stronger conclusions. A similar pattern is observed in Figure 3.3(c): the quantities of interest in authoritarian compared to democratic regimes are characterized with a slightly greater excess of 0s and 5s though such a difference lacks statistical significance.

To better understand the baseline for comparison, it's also critical to construct the barplots for all the participants across the country-year electoral races. Figure D.1(a) in Appendix D shows an excessive appearance of 0s in the percentages compared to other anomalies. Specifically, in authoritarian regimes compared to democratic ones, the number of 0s in the percentages is not only greater, but also statistically significant, which is also supportive of my theoretical expectations (Figure D.1(c)). In Figure D.2 in Appendix D yielding the comparison of the last digits in turnout across different systems the bars look quite complicated: while in the states with unelected local agents the proportion of 0s in the percentages is smaller than with elected, the systematic excess of 0s in the unitary states over the federal ones is observed.

The results from my multivariate analysis are reported in Table 3.5.[21] A set of find-

[21] Nonlinear least squares estimates for all the models:
$\texttt{Revenues}_{it+1} = b_0 + b_1\texttt{Yr2005}_{it} + b_2\texttt{Yr2011}_{it} + b_3\texttt{Rallies}_{it} + b_4\texttt{GDP Growth}_{it} + \lambda_{it} + \lambda_{it}(f_0\texttt{fraud0s}_{it} + f_5\texttt{fraud5s}_{it}) + e_{it}$,

Table 3.5: Effects of *Institutional Loyalty* and Election Frauds on Financial Centralization ($Revenues_{t+1}$) [a]

	M(P05)	M(C05)	M(T05)	M(F)
Const b_0	0.042*	0.019	0.034	0.04
	(0.022)	(0.024)	(0.045)	(0.025)
Rallies b_1	-0.004**	-0.004**	-0.004***	-0.005**
	(0.002)	(0.002)	(0.001)	(0.002)
GDP growth b_3	0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Year2005 b_4	-0.005	-0.006	0.003	-0.005
	(0.008)	(0.008)	(0.011)	(0.007)
Year2011 b_5	-0.002	-0.003	0.003	-0.002
	(0.008)	(0.008)	(0.009)	(0.008)
Appointed a_1	0.007	0.003	0.088	0.006
	(0.097)	(0.097)	(0.109)	(0.09)
Revenues(Electoral) a_2	4.668***	4.553***	4.811***	4.563***
	(0.212)	(0.222)	(0.579)	(0.202)
Polity a_3	-0.241***	-0.231***	-0.262***	-0.239***
	(0.014)	(0.013)	(0.03)	(0.012)
Presidential a_4	-0.108	-0.126	-0.245**	-0.121
	(0.106)	(0.1)	(0.105)	(0.103)
Federalism a_5	-0.098	-0.095	-0.012	-0.085
	(0.079)	(0.074)	(0.094)	(0.071)
Fraud 0s f_0	-0.081	0.1	-0.05	
	(0.08)	(0.066)	(0.072)	
Fraud 5s f_5	-0.099**	0.045	-0.042	
	(0.04)	(0.062)	(0.079)	
Fraud f				-0.094***
				(0.025)
$\hat{\sigma}$	0.03	0.031	0.031	0.03
N	107	107	64	107

Notes: Cluster robust standard errors in parentheses. Significance levels: *p $\leq$ 0.1, **p $\leq$ 0.05, ***p $\leq$ 0.01. The models include the measure of fraud: M(P05) – the proportion of 0 or 5s in the vote shares of the winners; M(C05) – proportion of 0 or 5s in the vote counts of winners; M(T05) – proportion of 0 or 5s in the percentages of turnout; M(F) – the binary indicator of election fraud from *Database of Political Institutions*.

ings shown in the table are supportive of my hypothesis that financial rewards can be connected to the signaling strategies of the regional authorities. For instance, in Model *M(P05)* the effect of f_5 yields statistically significant negative effect on financial centralization -0.099% (significant at the 0.05 level). These findings elucidate the fact that signaling strategies conditional on $\hat{\lambda}$ seem to affect the successive allocation of financial resources in the regions: 1% increase in 5s contributes to almost 0.10% increase in reallocation of revenues to the regions, holding all other variables constant.

Additional empirical support for my findings is provided by my auxiliary model *M(F)*, utilizing the observer-based measure of fraud: it yields statistically significant negative effect of election fraud on financial centralization. According to model *M(F)*, if a governor moves from a clean election to a fraudulent election, the country average of regional revenues increases by 0.084 points, holding all other variables constant. Across all the computed models in Table 3.5 the regime's lower democracy score seem to be predictive of higher levels of financial decentralization.

Table 3.6[22] reporting the effects of election fraud on financial centralization expressed in tax effort also shows the presence of statistically significant effects of 0s and 5s in the direction predicted by my theory. Specifically, in Model *M(P05)* a 1% increase in the winner's vote percentage of 5s contributes to 0.29% increase in financial allocation of tax effort favoring the regions; in Model *M(T05)* 1% increase in 0s of turnout results in 0.21% rise in financial allocation of tax effort favoring the regions. Finally, the direction and significance of explored effect also holds for the alternative measure of fraud in *M(F)*.

The overall results of analysis are reported in Table D.1 of Appendix D. This table utilizes results from the models presented in Table 3.5. For each of the country groups I

$$\lambda_{it} = \frac{1}{1+\exp\{-(a_1\texttt{Appointed}_{it} + a_2\texttt{Revenues}_{it} + a_3\texttt{Polity}_{it} + a_4\texttt{Presidential}_{it} + a_5\texttt{Federal}_{it})\}}$$

[22] Nonlinear least squares estimates for all the models: $\texttt{Tax Effort}_{i+1t} = b_0 + b_1\texttt{Yr2005}_{it} + b_2\texttt{Yr2011}_{it} + b_3\texttt{Rallies}_{it} + b_4\texttt{GDP Growth}_{it} + \lambda_{it} + \lambda_{it}(f_0\texttt{fraud0s}_{it} + f_5\texttt{fraud5s}_{it}) + e_{it}$,

$$\lambda_{it} = \frac{1}{1+\exp\{-(a_1\texttt{Appointed}_{it} + a_2\texttt{Effort}_{it} + a_3\texttt{Polity}_{it} + a_4\texttt{Presid}_{it} + a_5\texttt{Federal}_{it})\}}.$$

Table 3.6: Effects of *Institutional Loyalty* and Election Frauds on Financial Centralization (*Tax Effort*$_{t+1}$) [a]

	M(P05)	M(C05)	M(T05)	M(F)
Const b_0	0.057	-0.015	0.001	0.033
	(0.054)	(0.037)	(0.054)	(0.027)
Rallies b_1	0.002	0.002		-0.004
	(0.004)	(0.004)		(0.004)
GDP growth b_2	-0.004	-0.004		-0.003
	(0.003)	(0.003)		(0.003)
Year2005 b_3	-0.002	0.015	-0.008	-0.005
	(0.029)	(0.014)	(0.029)	(0.016)
Year2011 b_4	-0.035	-0.023	-0.019	-0.011
	(0.035)	(0.029)	(0.033)	(0.022)
Appointed a_1	-0.303	-0.3	0.204	0.008
	(0.195)	(0.205)	(0.102)	(0.138)
Revenues(Electoral) a_2	6.125***	6.454***	5.766***	4.871***
	(1.108)	(1.2)	(0.693)	(0.454)
Polity a_3	-0.311***	-0.318***	-0.322***	-0.258***
	(0.052)	(0.057)	(0.033)	(0.02)
Presidential a_4	0.035	-0.047	0.139	0.047
	(0.188)	(0.169)	(0.4)	(0.098)
Federalism a_5	-0.223	-0.184	0.374***	0.001
	(0.189)	(0.172)	(0.091)	(0.091)
Fraud 0s f_0	-0.316	0.191	-0.211**	
	(0.228)	(0.137)	(0.098)	
Fraud 5s	-0.157	-0.21	-0.039	
	(0.147)	(0.208)	(0.135)	
Fraud f				-0.064**
				(0.031)
$\hat{\sigma}$	0.448	0.45	0.056	0.045
N	74	74	37	74

Notes: Robust standard errors in parentheses. Significance levels: *p $\leq$ 0.1, **p $\leq$ 0.05, ***p $\leq$ 0.01. The models include the measure of fraud: M(P05) – the proportion of 0 or 5s in the vote shares of the winners; M(C05) – proportion of 0 or 5s in the vote counts of winners; M(T05) – proportion of 0 or 5s in the percentages of turnout; M(F) – the binary indicator of election fraud from *Database of Political Institutions*.

computed the mean predicted probability of loyalty on financial punishment.[23] The table displays the means and standard errors of predicted probabilities, across the different political regimes and systems of government.

Unfortunately, because of the data limitations I was unable to estimate the mean effect of loyalty on punishment in the federal setting.

As one moves from the democracy to autocracy, the mean predicted probability of the effect of institutional loyalty on financial punishment increases. Thus, autocracies are characterized with greater signaling patterns, compared to democracies, confirming **Hypothesis** 2. The comparison of mean effects between the federal and unitary states in democracies shows a distinctive effect of loyalty on financial punishment in the federal states than in the unitary states: counter to my theoretic expectations the signaling patterns seem to be prevalent in the unitary states compared to the federal ones. Thus, **Hypothesis 3** has not been confirmed by my empirical analysis: unitary states demonstrate stronger signaling patterns compared to federal ones.

3.6 Conclusion

My basic empirical findings suggest that theoretical implications from the formal signaling model are supported by the data.

The data analysis from the Russian presidential elections shows strong evidence of election fraud associated with the interbudgetary transfers. For elections from 2000 and on, and very clearly for the elections of 2004 and 2008, I am confident that there is widespread fraud motivated by governors' desire to signal their individual loyalties to Kremlin. The fact that the signaling in 2004 is apparent in both territory-level and precinct-level turnout data suggests that many officials besides merely governors or local agents are involved in the frauds. Likely hierarchies of signals are involved. The

[23] $\hat{p}_\lambda = \dfrac{1}{1+\exp\{-(a_1\texttt{Appointed}_{it} + a_2\texttt{Revenues}_{it} + a_3\texttt{Polity}_{it} + a_4\texttt{Presidential}_{it} + a_5\texttt{Federal}_{it})\}}$

signaling patterns with turnout and incumbent's vote percentage in 2008 are apparently well-connected to postelection rewards. This tells us something about how election fraud activities by 2008 have become even more completely federalized in ways that go beyond the scope of the game model.

In a broader perspective my analysis suggests that institutional change over time associated with Putin's recentralization policies in the 2000s also impacted the structure of election frauds in Russia. In terms of the game model, the value of the parameter d, the value to the Leader of replacing a disloyal governor, greatly increased. As recentralization gained hold, the threat associated with transfers to regions often decreased—the threat of regional secession disappeared—so that the long-run returns associated with transfers likely often increased: b was less often negative or at least often less negative. These changes changed the strategies governors and the Kremlin found optimal, leading to the situations seen in 2004 and 2008, where election frauds are easy to detect because governors use them to send signals to the Kremlin. As has been shown, in Russia, the occurrence of zeros or fives as the last digit in turnout and vote percentages is connected to an extensive signaling structure wherein election frauds are connected to postelection rewards and punishments, confirming my **Hypothesis 1**.

My game-theoretical propositions have been also adjusted to cross-national data analysis by classifying equilibria profiles from the signaling game across multiple political regimes. The empirical analysis based on unique original datasets helps us to draw two important conclusions. First, specific signaling patterns seem to be prevalent in cross-national data as well as in the Russian data: abundance of zeros and fives contributes to growing financial decentralization, i.e. leading to more resources concentrated in the regions. Second, in accordance with my theoretical expectations, autocracies are characterized by greater signaling patterns than democracies, confirming **Hypothesis** 2. Moreover, counter to my theoretic expectations, the signaling patterns seem to be prevalent in the unitary states compared to the federal ones, rejecting **Hypothesis 3**. Although the implications from the formal model are suggestive of Hypothesis 3, intuitively it seems plausible that the unitary states are expected to show greater signaling patterns compared to the federal ones, because of the stronger hierarchies and larger consolidation of resources in the center. The observed complexity in interpretation of results may be also due to classification errors and subsequent misattribution of equilibria profiles to specific regimes.

Although this research employs multiple robustness checks for both the Russian and cross-national data, it has several important limitations. First, analysis of the cross-national data has been performed using regional level data, however, data scarcity with respect to the proxy of transfers has led to the aggregation of all data to the national level. Second, convergence issues related to nonlinear models prevented me from utilizing the model including short-run distortion linearly, and led to substituting it with its nonlinear equivalent. In the future more fine-grained data will mostly likely resolve these issues. Even though all these limitations are substantial, my empirical analysis demonstrates strong applicability of the signaling games of election fraud to the Russian case, and to a broad range of political regimes, in particular, to autocracies and unitary democracies.

CHAPTER IV

Theory of Credibility: Linking Preference Falsification and Election Fraud In Electoral Autocracies

4.1 Introduction

In elections under authoritarian rule, the ruling party or an incumbent usually enjoy overwhelming electoral support, with the elections often considered fraudulent (Diamond 2002). Electoral autocracies or hybrid regimes combine democratic and authoritarian elements, masking the authoritarian nature of the regime with democratic political institutions, such as multi-party elections. These regimes conduct public opinion polls in addition to holding elections, and surprisingly, a close match between public opinion polls and election results is often observed, even when obvious vote stealing takes place. What is the general mechanism behind a close match between the polls and the rigged election results? Can pre-election polls constrain the autocrat's ability to commit election fraud? Can pre-election polls be used as a reliable way to detect election fraud? The answers to this set of questions are consequential to our understanding of how elections are organized in electoral autocracies, and of how helpful the polling data can be as a tool of election fraud detection in democracies (Charnin 2012). Indeed, the importance of pre-election polling is hard to overestimate, since a single opinion poll can serve as a coordination mechanism, having a significant influence on election outcomes and allowing the incumbent to guarantee the credibility of rigged election results (Andonie & Kuzmics 2012).

The electoral research on preference falsification is usually focused on misprediction of the final outcomes by the pollsters (Bischoping & Schuma 1992). However, no research has focused, so far, on the striking accuracy of election polls in electoral autocracies when the presence of election fraud is common knowledge among the populace. Major national polling organizations issued election forecasts based on Putin's electoral ratings that successfully predicted official election results within the margin of error (See Table E.1 in Appendix E). Surprisingly, however, despite his high popularity oftentimes driven by exaggeration of external threats and terrorist dangers (Arce 2003; Ekman 2009; Mansfield & Snyder 1995) election fraud has always been an integral part of his presidency, and is characterized by an upward trend over Putin's time in office (Mebane & Kalinin 2009a). This especially applies to the most recent Russian presidential election in 2012, which was marked by the spread of massive protests associated with the growing public awareness of alleged election fraud and a substantial voter mobilization effort (Enikolopov et al. 2013; Kalinin 2016; Kalinin & Shpilkin 2012; Shpilkin 2011).

The observed close congruence between Putin's official electoral support and the polling election forecasts has three explanations: (1) in reality the election fraud has never occurred, therefore the election polls are correct; (2) since a significant amount of election fraud is present, the election polls are incorrect; and (3) both electoral results and election polls are fabricated and therefore fraudulent. Based on anecdotal evidence from election observers and scholarly research, this chapter argues that the second explanation provides the most plausible argument.

There are many reasons for which polls can be incorrect in electoral autocracies, from crude data fabrication to issues with the sampling frame. The abuse of non-probability sampling design can contribute to unintentional upward inflation. Measurement error, specifically social desirability bias (or preference falsification), can inflate the incumbent's election ratings due to the respondents' eagerness to portray themselves in a socially desirable way. Two explanations can be readily excluded. Previous research on the 2012 presidential election indicates that the non-probability sampling design used by a majority of the organizations cannot explain the observed inflation in the estimates (Kalinin 2014a). Since across all the survey organizations, with a range of relationships to the Kremlin, polling estimates vary within the margin of error, it is unlikely that data fabrication took place. The final explanation is linked to the preference falsification. It implies that respondents give dishonest answers to conform to societal norms, thus contributing to an increase in response bias in the autocrat's electoral ratings.

This chapter provides an innovative perspective on the mechanism by which the autocrats in electoral autocracies strategically benefit from preference falsification, which boosts their own electoral ratings and encourages perpetration of election fraud. By doing so, the autocrats are able to organize election fraud up to the level of the discrepancy, effectively hiding the extent of election rigging and avoiding the political risks associated with revealed mismatch. Ideally, the presence of the observed close match between polling forecasts and election results enables the autocrat not only to claim his electoral legitimacy validated by pre-election polling, but also to reveal the weaknesses of political opposition unable to enjoy such extensive public support.

If, however, any of such mismatches occur these goals are severely undermined. Politically sensitive questions in pre-election polls in electoral autocracies and democracies have been studied in a fairly large body of literature (Anderson 1994; Beltran & Valdivia 1999; Bischoping & Schuma 1992; Geddes & Zaller 1989; Sieger 1990). This literature is usually focused on misprediction of the final outcomes by the pollsters due to contextual effects related to the authoritarian nature, flaws in sampling, last minute changes in preferences or preference falsification. For instance, according to Bischoping and Schuma (1992) almost all polls in Nicaragua forecasted a clear victory for the incumbent Sandinistas, but their opponent won the race, which was attributed to the preference falsification due to the perceived partisanship of a poll by the respondents.

Theoretically, this chapter builds on Timur Kuran's work on preference falsification, by adjusting his basic model to the topic of election fraud (Kuran 1987, 1991). Within this framework, election fraud is designed to mask the discrepancy between endogenously determined public and private pre-electoral preferences, and guarantee the autocrat a stable equilibrium. My theory suggests that election fraud serves as a by-product of pre-election forecasts that are contaminated with the preference falsification, creating leeway for numerous electoral violations, including election fraud. Theoretical implications of the model are tested on empirical data from the 2012 Russian presidential elections, thereby opening the door to empirical estimation of election fraud by means of election polls and survey experiments. In order to extend my findings beyond the Russian case and perform robustness checks of my main findings, I also apply a statistical analysis of cross-national data.

The contribution of this chapter to the existing literature is threefold. First, this chapter extends Kuran's model by adding to the model the concept of election fraud, and thus offers a mechanism by which an incumbent insures his most desirable electoral outcome. Second, this chapter tests the theoretical implications of the model by utilizing original survey data collected by the author in Spring 2012 during the Russian presidential campaign. In contrast to conventional election forensics research, which does not consider the dimension of public opinion surveys, this research demonstrates strong empirical findings with respect to the effect of preference falsification on the level of election fraud in electoral autocracy. Third, I compare the reliability of two types of election fraud indicators: two digit-based tests and the model-based measure of election fraud.

The structure of this chapter is as follows. Section 4.2 discusses three key actors involved in the mechanism linking preference falsification with election fraud, while reviewing the literature on this topic. Section 4.3 describes the specifics of Russian context and provides detail on the organization of election fraud in Russia. Section 4.4 provides an overview of research on the preference falsification or social desirability bias in Russia. Section 4.5 offers a short description of Kuran's model of preference falsification adapted for the topic of election fraud, and presents an empirical analysis of the model's implications by employing the Russian and cross-national data. In the final part I draw conclusions and discuss prospects of future research.

4.2 Theory of Election Fraud and Preference Falsification

In the combined theory of election fraud and preference falsification, there are three key actors: the voter/respondent, the autocrat and the survey organization. All three actors are affected by pre-election polling: the voter/respondent by falsifying his preferences and inadvertently instilling a pro-incumbent bias in the polls, the autocrat by organizing election fraud aimed to match the magnitude of pro-incumbent bias, and the survey organization by computing biased electoral ratings and making them accessible to the general public.

Voter/Respondent The importance of pre-election polling in a voter's strategic choice has been the subject of several studies. Since elections with voters acting strategically typically have multiple equilibria, they exacerbate a coordination problem (Kuran 1991; Palfrey 1989), which can be alleviated by pre-election polls. For example, the experimental evidence described in Forsythe, Myerson, Rietz, and Weber (1993) suggests that elections can be regarded as a function of poll results: through the polls the majority can guarantee itself the most favorable outcome. Usually, however, more precise information about pre-election preferences can result in a drastic increase in turnout, thus boosting the aggregate cost and reducing total welfare (C. R. Taylor & Yildirim 2010). The authors argue that pre-election polls can be used by voters as an equilibrium selection device in which the respondents truthfully indicate their favorite candidate. The lying respondent, however, triggers a non-coordinated outcome, thus increasing the probability of an outcome with a tie and consequential payoff loss. From this perspective the strategic behavior of respondents enables them to use a chance of being selected into the survey as a way to influence the voting decisions of other voters.

Theories based on the general model of voting and polls are built on the assumption of guaranteed anonymity and privacy for the respondents, when there are no external threats inhibiting them from openly sharing politically sensitive information with the survey organization. In an authoritarian setting, however, the respondents might fear repercussions for failing to mention the "right" candidate. If these fears persist, respondents will be inclined to falsify their preferences, thus reducing the probability of the desirable outcome to the voters and consequently increasing the probability of the desirable outcome to the autocrat. Besides high repression costs for the support of opposition due to the coercive capacity of the state, additional incentive for respondents to falsify their preferences can be associated with the small probability of tied elections in such regimes, thus reducing rational benefits for sharing truthful information about such elections (Way & Levitsky 2006). Moreover, because the regime controls ballot access, credible opposition candidates can be left off the ballot, thus inducing the respondents to make suboptimal choices with low-valued outcomes. In such cases, the respondents can be prone to falsifying their preferences in favor of the autocrat. This affects pre-election polls and exacerbates a coordination problem, in which the majority cannot guarantee itself the most favorable outcome and the autocrat enjoys an increase in the likelihood of his most preferred outcome.

The concept of preference falsification implies that respondents give dishonest answers to conform to societal norms and to not be embarrassed by their responses, thus contributing to an increase in response bias and measurement error. It has long been a subject of survey research literature (Couper, Singer, & Tourangeau 2003; Dillman & Tarnai 1991; Groves & Kahn 1979; Tourangeau & Smith 1996). Kuran's theory of preference falsification is especially helpful for our understanding of how electoral preferences can be endogenously determined in electoral autocracies (Kuran 1991). According to Kuran, the incentive of an individual to reveal his private preference is a function of the size of public opposition and psychological cost of preference falsification. With the growth of public opposition, while keeping private preferences constant, there comes a point where his external cost of joining the opposition falls below his internal cost of preference falsification (i.e. bandwagon effect) (Kuran 1991, 18). For instance, according to mail surveys in the Soviet Union, the presence of preference falsification and low response rates could be largely attributed to the consequences the Soviet citizen could face if his political reputation were negatively affected. Authoritarian regimes are always concerned about preference falsification and try to keep themselves informed about the private preferences of their constituencies, by withholding and manipulating certain parts of data from polls (Otava 1988), thus contributing to the rise of "spiral of silence" (Noelle-Neumann 1984).

Autocrat In the pre-election period, the autocrat is well-motivated to exploit all resources to remain in power. He may use violence, polls, and media in an effort to prevent an unfavorable electoral outcome, by weakening the opposition and solidifying his own political dominance. Indeed, repression of various information channels, providing the opposition and the citizenry with information on the relative balance of power, loyalty and dissatisfaction, helps an autocrat to deter the emergence of any possible challengers and minimize his own political risks (Egorov et al. 2009; M. K. Miller 2014; Wintrobe 1998). However, this impacts the autocrat as well, since political transparency is often seriously circumscribed, leading to information shortages, inefficiency, and low quality of the public policies. One reliable information channel is local elections, which the autocrat regards as an important trial ground for handpicked successors (Boix & Svolik 2007; Magaloni 2010; Malesky & Schuler 2010; Reuter & Robertson 2012).

Another alternative to consider are public opinion polls. As a rule, in electoral autocracies public opinion polls conducted by polling organizations tend to help autocrats to gauge their popularity prior to an election, and, ideally, serve the goal of creating a public impression of his own political dominance, which might discourage the political opposition from its quest for power (Gel'man 2005; Lohmann 1994; Simpser 2005, 2013). As Lohmann (1994) points out, repression and censorship enable an autocrat to maintain negative information within the private domain, thus preventing political entrepreneurs from taking advantage of it to mobilize the opposition. In this sense election polls can be especially useful for an autocrat if they contain a survey error that inflates the autocrat's public support. The autocrat can also rely on diversification of data sources by engaging security agencies in the polling, though given the methodological opaqueness of the data collected by these agencies, its quality is unknown and its reliability is often compromised (Birukova & Nikol'sky 2014). If, however, public opinion polls are known to be anticipatorily unreliable, the incumbent might have difficulty estimating his true popularity. He may therefore be over-responsive towards the threats from the opposition and may excessive violence or election fraud, as a result potentially undermining his own prospects of political survival (Hafner-Burton, Hyde, & Jablonski 2013). For instance, elections in Zimbabwe (2000-2008) show how the lack of reliability of pre-election polls within the suppressed informational environment motivated Mugabe to employ tactics of election violence and fraud (Hafner-Burton et al. 2013).

Survey organization Since some survey errors can be beneficial to the autocrat, he might try to encourage false polling data through bad polling techniques or crude data fabrication. There are two important constraints making this strategy suboptimal. One constraint is related to autocrat's interest in obtaining private information about his genuine support. Knowing this, the survey organization would be interested not so much in wholesale fabrication of data, but rather in data collection that would permit derivation of "quantifiable" biases and errors, making it possible to extract the genuine information from the biased estimates. This strategy encourages the survey organization to utilize relatively cheap survey techniques in its polls, which permit extraction of valuable pieces of information to be shared with the autocrat. This enables the survey organizations to substantially cut back on data collection costs by conducting the survey only once, and at the same time send separate information signals to the general public and the autocrat. As a result, while the general public receives inflated estimates based on the respondents' public preferences, in contrast, the autocrat receives deflated estimates based on the respondents' private preferences.

Another constraint prohibiting survey organizations from data fabrication is associated with reputation costs. For instance, organizations such as Levada-Center extensively work with foreign customers interested in the high quality data. Levada-Center periodically conducts the Omnibus survey, utilized in this research, with a mix of questions from both foreign and domestic clients. This incentivizes Levada-Center to exercise quality control over the entire data collection cycle. Therefore unlike other survey organizations, Levada-Center being financially independent from Kremlin can be viewed as least interested in data fabrication. However, Levada's electoral forecast for Putin's support turned out to be higher than those issued by state-controlled organizations that are presumably more prone to fabricating data. This observation indirectly refutes the notion that all forecasting data produced by the survey organizations can be easily fabricated in the autocrat's interest.

4.3 Context

During Vladimir Putin's presidency in the 2000s, growing authoritarian tendencies in Russia exacerbated the problem of blatant election fraud in favor of pro-Kremlin candidates and parties (Buzin & Lubarev 2008; Enikolopov et al. 2013; Kalinin & Shpilkin 2012; Kobak et al. 2012; Kobak, Shpilkin, & Pshenichnikov 2016; Mebane & Kalinin 2009a; Myagkov et al. 2009). Evidence of election fraud is based on multiple sources, such as electoral and survey data and observer reports. Statistical analysis of the Russian presidential election 2012 estimates election fraud reaching 5% for Putin's electoral support and 10% for turnout (Kalinin & Shpilkin 2012). Other studies show that in 2012 the estimated proportion of precincts with the election fraud reached about 40% Klimek et al. (2012), which seems to be an exceedingly high number to be even remotely believable.

The organization of election fraud is usually assigned to regional and local authorities. In federal states, such as Russia, federal elections are organized by regional authorities who are responsible for the provision of favorable electoral outcomes that match general social expectations in respective regions. This phenomenon became especially acute with Putin's centralization policies of the 2000s, which led to the cooptation of governors' "political machines" into the power vertical. As a result, political loyalty in addressing the Kremlin's political needs was regarded as a crucial quality for the governors. Although with the abolition of gubernatorial elections, the costs for committing fraud by the governors were reduced because the credibility of electoral outcomes could be guaranteed by their close match with the regional pre-election polls. To comply with Kremlin's expectations, the regional governors can resort to a broad range of methods, such as ballot stuffing, ballot switching or protocol tampering (Harrison 2009). All three methods of election fraud are widely used in Russia, with the first two methods used on the level of precincts and the third, at the level of territorial commissions.

Since the manufacturing of results is not directed from the Kremlin, the regional variation in Putin's electoral support is expressed in standard deviation is 10%, ranging from 47% of electoral support in Moscow to 99% in Chechnya. Importantly, the abnormal zones of the Russian elections with reference to turnout and voting have almost always been associated with the ethnic regions, such as Republics of the North Caucasus (such as Chechnya), and rural areas where mobilization of political machines and clientelistic networks by the regional authorities has been most effective. According to this logic over time we expect to observe a "race to the top" with more election fraud and polling weakly associated with election results. However, this race has an additional constraint:

since electoral results must meet the credibility criteria, a "race to the top" has to be strongly associated with the bias in the regional election ratings. Otherwise, excessive election fraud can make election fraud easily detectable by the voters, consequentially raising the probability of mass protests and higher attributed costs to both the autocrat and the governor. While this observation is supported by analysis of Russian electoral data, demonstrating positive progression of electoral anomalies over time (Mebane & Kalinin 2009a) it has to consistently match the magnitude of the social desirability bias in election polls as well.

In sum, we would expect the following causal mechanism to be in place: by falsifying their preferences, respondents inadvertently instill a pro-autocrat or a pro-incumbent bias in surveys, which in turn incentivizes regional governors to mobilize their political machines for election fraud, in order to match the expectations expressed in the biased public polls and meet Kremlin's electoral expectations. In this mechanism the autocrat comes into play indirectly: by creating an unsafe polling environment, contributing to inflation of his public polls, and setting up the power vertical in which political loyalty in addressing the autocrat's electoral needs is regarded as a crucial quality for the governors.

4.4 A Study of the Social Desirability Bias

Noelle-Neumann's seminal work on the "spiral of silence" helps us to explore the mechanism by which social desirability evolves in autocracies, such as Russia (Noelle-Neumann 1984). It implies that when one faction in society possesses total public visibility while the other has been completely marginalized, the individual will assess the political climate personally or through the media. This assessment impacts the public behavior of an individual and her willingness to reveal her private political preferences. In particular, the revelation of her private preferences is less likely when an individual feels unsafe about expressing ideas contrary to official policy, or has a fear of isolation. Under these circumstances she will be inclined to falsify her political preferences in favor of those she thinks are acceptable to the public, or simply withdraw from discussion (Noelle-Neumann 1984, 5). For instance, the general setting of the Russian presidential elections 2012 with the incumbent's dominant position was likely to trigger sensitivity to questions related to his electoral support; supporters of political opposition, being in the minority, would feel pressured to remain silent or to falsify their preferences in favor of the incumbent.

This research will be primarily focused on testing the central implication of the "spiral of silence" theory: on inflation in the estimates of the incumbent's electoral support. The concept implies that polled individuals may give dishonest answers to conform with societal norms and so as not to be embarrassed by their responses, thus contributing to an increase in response bias and measurement error.

According to Tourangeau, Rips, and Rasinski (2000, 257) the "notion of sensitive questions presupposes that respondents believe there are defining desirable attitudes and behaviors, and that they are concerned enough about these norms to distort their answers to avoid presenting themselves in an unfavorable light". In this work I'll refer to the concept of "social desirability bias" every time I discuss the response bias of survey respondents from the perspective of the survey methodology literature. Social desirability and self-censoring can substantially affect respondents' responses due to social sanctions and risks arising from the respondent's decision to voice her support for the opposition or contentious opinions (Tourangeau et al. 2000). When there is almost no benefit in answering the questions truthfully, the individual would be more likely to subscribe to this strategy (Corstange 2009, 2-3). Also, there is a concept of "preference falsification", which according to Kuran "is the act of misrepresenting one's genuine wants under perceived social pressures" (Kuran 1991, 37-57). Since the concept of "preference falsification" is more conceptually grounded in political science literature, I'll be referring to it when I focus on my theory.

With respect to voting and voter turnout, social desirability has been explored in the works of Streb, Burrel, Frederick, and Genovese. (2008), Belli, Traugott, and Beckmann (2001), Holbrook and Krosnick (2010a, 2010b), Comsa and Postelnicu (2012). In their cross-national study of turnout in several democracies, Karp and Brockington (2005) find that in national settings with higher levels of participation, the tendency to over-report turnout is greater than in settings with low participation levels. There are several studies focused on survey experiments in an authoritarian setting. Weghorst (2011) in his paper on support for opposition violence against an incumbent party shows the difference between the results from direct and indirect self-reporting. Gonzalez-Ocantos, de Jonge, Melendez, Osorio, and Nickerson (2011) provide evidence showing that after the 2008 Nicaraguan municipal elections, a direct question on vote buying, compared with responses from a survey experiment, clearly underestimated the proportion of those who reported this behavior.

How much social desirability bias would we expect to find in our study? In their research Karp and Brockington (2005) by comparing official voting records with survey responses on turnout from several democracies conclude that the social desirability bias in democracies not only positively correlates with the turnout rate, but also demonstrates high levels reaching 27% for Britain, 26% for Sweden and 40% for the US. Turning to incumbent support, since other mature democracies have nothing like the problem that the US has in terms of information and bandwagon effects with regard to incumbent's support, the U.S. seems to be the most appropriate case for such comparison. For instance, in the U.S. presidential election there appears little bias, reaching 1.5%. For the House of Representatives and U.S. Senate races it's slightly higher, reaching 4%, for gubernatorial races it's about 5% (Wright 1993, 295).

Which U.S. election can be taken as a benchmark for our analysis? Since the Russian presidential election belongs to the low information environment where it is likely that many will not have heard of any candidate apart from the front-runner, as a benchmark the measure from similar setting needs to be taken. Even though at first glance the

U.S. presidential elections seem to provide the most plausible benchmark for comparison, their high salience and competitiveness make such comparison disputable. Instead, however, by taking into consideration the U.S. gubernatorial and congressional elections, known for their low salience and strong incumbency effects, I thus find the most appropriate way of handling this problem. Presumably, if the inflation in turnout exceeds 30 percent or in Putin's votes yields the estimate of 20-25% (i.e. exceeds 5%) one can argue that there is no doubt about the significance of the additional bias found in Russia. I surmise that any such discrepancy is due in large part to "spiral of silence" motivations. Thus my hypothesis is a follows:

Hypothesis 1: *Due to social desirability effects, Russian presidential elections in 2012 were characterized by a substantial inflationary bias in the estimates for incumbent and voter turnout, exceeding the democratic benchmark of 5% for the incumbent's support and 30% for turnout.*

Another question of interest is related to the variability of the social desirability bias across different demographic subgroups. Individuals displaying high levels of social desirability bias in contexts analogous to support for Putin are those who are relatively isolated, with weaker self-confidence, less interest in politics, and fear disrespect or unpopularity. Among those most disposed to speaking out publicly are rather men than women, younger people than older ones, those belonging to a higher social strata than those from lower strata (Noelle-Neumann 1984, 24). However, when it comes to turnout, a number of studies have found that individuals most likely to overreport voting have the same characteristics as those likely to vote: those who are highly educated, supportive of the regime, higher-status individuals are most likely to falsify their preferences in a survey (Bernstein, Chadha, & Montjoy 2001; Silver, Anderson, & Abramson 1986). They are more likely trying to create a good impression on the interviewer and feel pressured to vote, leading to a greater desire to falsify their responses. Those respondents for whom the norm of voting is most salient will be most likely to overreport their preferences.

Hence, here I formulate different hypotheses for Putin support than for turnout:

Hypothesis 2.1: *The social desirability bias in estimates for an autocrat's electoral support is expected to vary across different social groups: women, the elderly, persons with low education and the poor are expected to exhibit greater levels of misreporting compared to men, the young, those with higher education and the wealthy.*

Hypothesis 2.2: *Overreporting individuals with respect to voter turnout are expected to have the same demographic characteristics as the likely voters, i.e. those individuals who truthfully report having voted (highly educated, supportive of the regime, higher-status individuals)*

The next question is related to the temporal persistence of preference falsification throughout the electoral campaign. Here by the temporal persistence of the social desirability bias I mean the situation in which the magnitude of the social desirability remains unchanged throughout the campaign while the pre-electoral expectations of the incumbent's electoral support closely match the incumbent's official post-electoral outcome. According to Noelle-Neumann (1984, 31) one might expect a recognizable pre-election tendency of people claiming they are going to vote for the incumbent, but a post-election tendency to claim support for the incumbent can be even more salient, with a greater proportion of people falsifying their preferences. This comes as no surprise, especially, when the autocrat has managed to manufacture much of her official electoral support, thus creating the illusion of enormous popularity contrasted with the chronic weakness of political opposition (Simpser 2013). If, however, the autocrat did worse in the elections than pre-election polls reported, the magnitude of social desirability bias would most likely decrease and contribute to the growth of public opposition (Kuran 1991, 18). Since Putin's official results matched public expectations quite well, I expect the presence of temporal persistence of preference falsification to be without any significant changes between pre- and post-electoral periods.

Hypothesis 3: *For pre-election and post-election polls, one can expect the presence of temporally persistent social desirability bias for both voter turnout and incumbent's electoral sup-*

port.

4.4.1 Analytic strategy

Social desirability bias can be simply understood as the difference in the probability of the socially desirable response and the honest response, where anonymity is strictly guaranteed. While the socially desirable response is measured by direct questioning technique, the honest response is measured by indirect techniques. My analytic strategy employs both types of techniques, making it possible to measure the magnitude of the social desirability bias. Indirect questioning techniques are specifically designed to offer respondents an opportunity to answer truthfully without a fear of retribution. A list experiment or item count technique (ICT), which is a type of indirect questioning technique, uses random assignment of respondents to treatment and control groups(J. D. Miller 1984). According to the ICT, respondents are randomly assigned to two groups. One group serves as a control group, receiving both questions containing four statements each, while another group is a treatment group that receives both questions containing five statements (i.e. four non-sensitive items plus one sensitive). The share of respondents privately supporting Putin $\hat{s}_I$ is a standard difference in means estimator of two subsamples: $\hat{s}_I = \frac{1}{N_1}\sum_{i=1}^{N} T_i Y_i - \frac{1}{N_0}\sum_{t=1}^{N}(1 - T_i)Y_i$, where $N_1 = \sum_{i=1}^{N} T_i$ is the size of the treatment group and $N_0 = N - N_1$ is the size of the control group (Blair & Imai 2012).

Many studies have shown that ICT provides a reliable control of the social desirability bias (Chaudhuri & Christofides 2007; Corstange 2009; Glynn 2013; Green & Kern 2012; Imai 2011; Tsuchiya 2005). Nonetheless, the technique has several established limitations. For instance, Kiewiet and Nickerson (2014) illustrate that ICT can provide extremely conservative estimates of high incidence behaviors; Glynn (2013) mentions its relative inefficiency and its failure to provide individual-level measures for the sensitive item. Moreover, the anonymity condition can be violated due to a ceiling effect (when all of the statements are chosen by a respondent) or a floor effect (when none of the statements is chosen), which can be partly overcome by increasing the length of the list (Holbrook & Krosnick 2010b; Tsuchiya, Kirai, & Ono 2007). While the core assumptions of the technique hold, list experiments can generate valid estimates of social desirability bias. However, violations of these assumptions can substantially undermine the validity of obtained results.

In the present study I have conducted two list experiments designed to measure genuine electoral preferences for Putin and voter turnout:

> *Here is the list of four/five assertions. Please, listen to them all and then tell me how many you agree with. Do not tell me which assertion you agree or disagree with, just give me the total estimate.*
>
> - I usually read at least one newspaper or magazine a week;
> - I want to see Russia as a country with high-living standards;
> - I can recall the name of the head of Russian Constitutional Court;
> - **I will vote [voted for] Vladimir Putin in the most recent Presidential elections (March 4);**
> - I am satisfied with the level of my income.
>
> I agree with ___ (number of assertions)
>
> *Here is the list of four/five assertions. Please, listen to them all and then tell me how many you agree with. Do not tell me which assertion you agree or disagree with, just give me the total estimate.*
>
> - *My family has a car;*
> - *I can recall the name of the head of the Federation Council;*
> - *I watch TV daily;*
> - **I will vote [I voted] in the most recent Presidential elections (March 4)***;*
> - *The level of pension in our country is quite high.*
>
> *I agree with ___ (number of assertions)*

4.4.2 Data and Measurements

The fieldwork stage of the project was conducted over a period of two months between early February and early April 2012. Three surveys were conducted by Levada-Center (Omnibus/Courier Study, February 17-20 and 24-27; March 2012), and one by the Demoscope (Russian Election Study, March-April 2012) with 1500-1600 respondents sampled for each survey (Colton, Hale, Kosolapov, Tonis, & Prudnikova 2014). The major characteristics of the surveys can be found in Table E.2 of Appendix E. First, the sampling design employed by Levada-Center is typically utilized by the majority of national survey organizations. It is based on a proportional stratified sampling with the selection of households completed by the random route method and the selection of respondents by using quota sampling. In contrast, Demoscope's sample is based on multistage probability sampling with respondents selected by the nearest birthday method. All the surveys encompass both direct and indirect (ICT or list experiment) questions on Putin's electoral support and turnout, thus making an estimation of social desirability bias possible. The ICT experiment was preceded by direct question asked 5-10 minutes earlier as in Droitcour et al. (1991), because of concerns on the part of the pollsters about the unforeseen effects of list experiments on the estimates derived from the direct question. Moreover, the ICT experiment on turnout preceded the experiment on voting, being 5-6 questions apart from the latter.

Table 4.1 contains a summary of weighted demographic characteristics across four surveys. The observed similarities in the table entries for some demographic characteristics are explained by the quota sampling method and post-stratification weights used to construct this table (For more information, see Table E.2 in Appendix E). By and large, the collected data samples illustrate the absence of large differences across key demographic indicators, with the exception of wealthy/poor and rural/urban category for the post-electoral dataset. In order to simplify subsequent empirical analysis, I resort to data pooling, first by producing pre-electoral and post-electoral datasets, and second, by producing one single dataset from all of the data.

Table 4.1: Demographic Characteristics of Respondents from Four Surveys, *in percentages*

	Survey 1	Survey 2	Survey 3	Survey 4	Survey 5
Gender					
Male	46.3	46.3	46.3	44.6	45.0
Female	53.7	53.7	53.7	55.4	55.0
Missing	0.0	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0
Age					
18-24	13.9	13.9	13.9	15.0	13.5
25-34	21.0	19.8	20.1	17.9	19.6
35-44	16.3	18.3	15.8	17.3	17.1
45-54	18.6	17.9	20.0	18.0	18.3
55-64	16.6	17.8	18.0	16.7	17.0
65-74	9.0	8.4	8.7	9.1	9.3
75 and older	4.5	3.9	3.5	6.0	5.2
Missing	0.0	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0
Education					
High school	70.7	70.7	70.7	67.6	69.25
College	29.3	29.3	29.3	31.6	30.61
Missing	0.0	0.0	0.0	0.8	0.14
Total	100.0	100.0	100.0	100.0	100.0
Well-being					
Wealthy	21.4	26.1	26.0	14.4	21.5
Poor	78.2	73.7	73.6	84.6	77.9
Missing	0.4	0.2	0.4	1.0	0.6
Total	100.0	100.0	100.0	100.0	100.0
Residence					
Urban	51.4	51.1	50.0	70.0	55.7
Rural	48.6	48.9	50.0	30.0	44.3
Missing	0.0	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0
Sample size	1601	1601	1633	1682	6517

Notes: Survey 1 – Levada(17-20 Feb.), Survey 2 – Levada(24-27 Feb.), Survey 3 – Levada(March), Survey 4 – Demoscope(March-April), Survey 5 –Pooled data.

In both cases my data pooling has been justified by a statistical testing procedure equivalent to a likelihood ratio test for the pooled and unpooled data samples. All the missing values in the independent variables have been replaced with the medians or means.

In their methodological study Blair and Imai (2012) list three identification assumptions for an ICT to be met: a) randomization of the treatment, i.e. randomization of respondents into the treatment and control groups; b) no design effect, i.e. the presence of the sensitive item in the list doesn't affect the way the respondent thinks about the control items; c) no liars, i.e. respondents share their truthful answers when asked an ICT question. Any violation of these assumptions can potentially lead to the failure of the list experiment, and thus distort the estimates. The overall quality of designed experiments is assessed on the basis of whether all three assumptions were satisfied.

For determining the overall validity of the conducted ICT experiment, I test the presence of any apparent violations in the key ICT assumptions, such as randomization of treatment and the absence of liars. The randomization assumption is tested by regressing treatment assignment on covariates using both pre-electoral and post-electoral datasets. Almost all of the covariates are statistically insignificant, which is indicative of successful randomization of the treatment (Table E.3). However, it has been impossible to achieve completely balanced treatment assignments. In both regressions one of the covariates turns out to be statistically significant: "Sex" in the case of the pre-electoral dataset, and "Wealth" in our post-electoral data. The assumption that the presence of floor and ceiling effects compromises anonymity has been also satisfied. According to Table E.4, depicting the frequencies of item counts for voting and turnout, this problem has been minimized by the proper pre-selection of non-sensitive items, which reduced the frequency with which 0s and 5s appear in the data. Finally, since it is impossible to empirically test the design effect assumption in my experimental setting, I am forced to make strong assumption about the absence of design effect in my analysis.

4.4.3 Results

My initial findings with respect to the means for direct and indirect ICT self-reporting (ICT) as well as the difference between them, i.e. social desirability bias (Δ) and associated bootstrapped standard errors are presented in Table 4.2. One of the potential challenges when using the ICT measures is the loss in efficiency of the estimator, i.e. computed standard errors for the list experiment are four times larger than for the direct self-report. In spite of this fact, the presence of a strong statistically significant social desirability effect is observed in both pre-electoral and post-electoral settings. The difference in means estimator (DIM section of the table) shows the percentage of pre-electoral support for Putin among the participants reaching 47.2%, with s.e. 4.2%, while the direct self-report yields the estimate of 66.1%(1.3%). The difference between both figures gives us the estimate of social desirability bias of 18.9%, which is different from zero at $\alpha = 0.05$ for a one-tailed t-test. The pre-electoral estimates for turnout show somewhat similar patterns: the indirect self-report yields an estimate of 50.7%(4.1%), and the direct technique yields 67.1%(1.0%). The difference of 16.5% is statistically significant. In addition, using Blair and Imai (2012)'s package on multivariate analysis of ICT, I also control for ceiling and floor effects (See "Modeled" section in the table). When using this control, even though the presence of social desirability seem to be prevalent for Putin's electoral support, the estimates for turnout seem to be more ambiguous. None of the social desirability estimates is statistically significant. Hence, my theoretical implications from **Hypothesis 1** are well supported by the data: both the difference in means estimator and the modeled portion of my analysis demonstrate the presence of strong social desirability bias only in the incumbent's estimates, though failing to agree in the case of turnout. Basic findings illustrate that the magnitude of social desirability bias with respect to turnout is quite comparable with democracies while with respect to Putin's support observed inflation turns out to be higher compared to democratic benchmark defined earlier.

The comparison of the pre-electoral and post-electoral estimates shows the absence

Table 4.2: Electoral Support Using Direct and Indirect Self-Report, *in percentages*

		Pre-electoral period			Post-electoral period		
		direct	indirect	Δ	direct	indirect	Δ
DIM	Incumbent(All)	45.3	28.5	**16.8**	47.8	34.6	**13.2**
		(1.1)	(3.7)	**(3.7)**	(0.9)	(3.2)	**(3.2)**
	Incumbent(Voted)	66.1	47.2	**18.9**	68.8	52.1	**16.7**
		(1.3)	(4.2)	**(4.3)**	(1.0)	(3.4)	**(3.6)**
	Turnout(All)	67.1	50.7	**16.4**	75.9	55.3	**20.6**
		(1.0)	(4.1)	**(4.0)**	(0.8)	(3.7)	**(3.7)**
Modeled	Incumbent(All)	67.1	42.2	**24.9**	68.6	36.7	**31.9**
		(6.5)	(16.3)	**(16.2)**	(7.9)	(16.0)	**(11.5)**
	Turnout(All)	72.9	64.7	**8.2**	75.6	72.6	**3.0**
		(6.4)	(24.5)	**(19.5)**	(10.7)	(24.5)	**(15.3)**
	Sample size		3202			3315	

Notes: DIM – estimates computed with standard difference in means estimator (weighted); Modeled – estimates computed using multivariate regression analysis with *list() package*. *Incumbent(All)* – percentage of Putin's supporters among all respondents; *Incumbent(Voted)* – percentage of Putin's supporters among those who intend to vote [voted]; *Turnout* – percentage of those who will vote [voted]. Monte Carlo standard errors are in parentheses. According to official election results, Putin received 63.6% of the popular vote, turnout reached 65.34%.

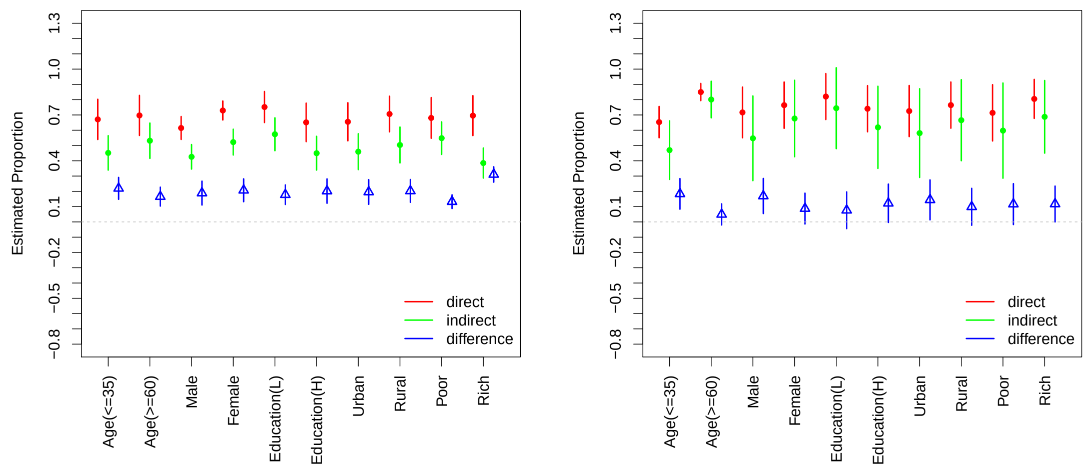
of statistically significant difference. Social desirability bias is persistent across both settings without any notable changes in the estimates. The statistically significant difference between pre-electoral 67.1%(1.0%) and post-electoral estimates 75.9%(0.8%) for voter turnout is the only exception to this. The observed higher levels of social desirability bias with regard to turnout reveals the growth in proportion of those who falsify their true preferences after incumbent's win, which is partly supportive of the "spiral of silence" theory. Thus, my **Hypothesis 3** seems to be also supported by the data.

Holbrook and Krosnick (2010b) argue that comparison between survey estimates and official estimates can be troublesome, because the numerous methodological problems associated with surveys – such as undercoverage, nonresponse – produce different kinds of survey biases in the estimates. However, it is still potentially useful to explore how well our survey estimates match the results from official statistics. According to official election results, Vladimir Putin received 63.6% of the popular vote with voter turnout reaching 65.34%. Both Putin's estimated support with the direct self-report and turnout for pre-election and post-election studies illustrate close proximity between the survey estimates and official statistics, a difference that is statistically indistinguishable from zero. Along with the basic difference-of-proportions estimates, I also resort to multivariate analysis to test the hypotheses about the levels of bias across different subgroups.

Here I implement the list-experiment models using the Blair and Imai (2012) maximum likelihood estimator, which enables me to obtain more efficient estimates of the social desirability bias. The set of predictors included in the model is as follows: sex, age, education, a measure of subjective well-being of an individual (also termed as wealth or rich vs. poor in the text) and type of residence (rural/urban). In order to make the results more readily interpretable, in the next stage I resort to computing individual-level measures of social desirability bias by finding the differences in predicted probabilities for direct (the binary logit model) and indirect responses(maximum likelihood estimator, as suggested by Blair and Imai (2012)). All measures have been aggregated up to the level of social groups by computing corresponding means and standard errors. Figures 4.1(a,b) depict the means as filled circles and 95% confidence intervals as solid lines for all three computed measures. The direction of social desirability bias is marked as upper/lower triangle characters, depending on the sign of obtained bias. Figure 4.1(a) illustrates that almost all of the estimated proportions are bounded between zero and one (with the exception of the rich category), which is consistent with our expectations. Specifically, Putin's public support is in line with the previous work, indicating that he is more likely to be publicly supported by richer than poorer, rural than urban residents (Rose, Mishler, & Munro 2011). Indeed, the social desirability bias is not evenly distributed across the sample population. In Figure 4.1(a) all social groups demonstrate high and statistically significant levels of social desirability bias: the rich, young and female demonstrate the highest values of social desirability bias while the poor, old, uneducated demonstrate the lowest.

The younger age group is likely to inflate their electoral support of Putin by 22%, and

Figure 4.1: Estimated Proportions for Voting and Turnout by Subgroups



(a) (b)

the old, by 17%. Men are likely to falsify incumbent support by about 19%, and women, by 21%. Those with higher education contribute to inflation by about 20%, and those with lower education, by about 18%. The poor seem to be least biased inflating their support for Putin by 13%, while the rich are the most biased, inflating it by 31%. A small distinction in the levels of the social desirability bias is observed between urban and rural residents. Since for Putin's electoral support, the likely voters — women and the rich — seem to demonstrate maximum (although not statistically significant) bias, **Hypothesis 2.1** is not well supported. The pattern of over-reporting for Putin's support is more like what would be expected for turnout, though not significantly so. Finally, Figure 4.1(b) representing turnout depicts that none of the distinctions appear significant apart from the distinction between young and old cohorts, male and female, urban and rural. Since most of the computed biases are statistically insignificant, we lack evidence to confirm or reject our **Hypothesis** 2.2.

4.4.4 Validation Study

In order to gain greater confidence in the result of the list experiment, I refer to an additional external validity check by utilizing an urns experiment, organized by one of the national pollsters (VCIOM) prior to the 2012 elections. The experiment is a street survey based on non-probability sampling design: on the first day a randomly chosen respondent is directly asked by the interviewer about her electoral preferences, while on the second day a randomly chosen respondent fills out a questionnaire by herself and drops it into an urn, thus ensuring anonymity of response. The geography of the experiment included four Russian regions (Moscow, St.Petersburg, Sverdlovskaya oblast' and Altayskiy kray), each containing four primary sampling units. The declared response rate is in the range of 54-68%.

Table 4.3: External Validity Check of Putin's Electoral Support, in *rounded percentages*

		Urns Experiment		ICT Experiment			
Regions	Official	Means		Mean differences		Model-based	
		Direct	Indirect	Direct	Indirect	Direct	Indirect
Moscow	47	56	51	46	42	49	61
		(52; 60)	(49; 53)	(29; 62)	(25; 58)	(30; 68)	(31; 90)
St.Petersburg	59	64	51	59	36	67	63
		(61; 67)	(48, 54)	(34; 85)	(11; 62)	(38; 97)	(35; 90)
Altayskiy kray	57	50	44	63	57	67	95
		(48, 52)	(42, 46)	(33; 92)	(28; 87)	(48; 85)	(63; 129)
Sverdlovskaya oblast'	65	72	59	52	13	62	88
		(70; 74)	(57; 61)	(8; 96)	(-31; 57)	(36; 87)	(26; 151)

Notes: Numbers in parentheses are 95% confidence intervals. Sample sizes for the urns experiment: Moscow(direct: 675, indirect: 2283) St.Petersburg(direct: 1284, indirect: 927), Altayskiy kray(direct: 2299, indirect: 2208), Sverdlovskaya oblast' (direct: 2346, indirect: 1578). Sample sizes for the pooled dataset: Moscow(direct: 346, indirect: 534), St.Petersburg(direct: 146, indirect: 218), Altayskiy kray (direct: 146, indirect: 205), Sverdlovskaya oblast' (direct: 68, indirect: 105).

The results of this analysis are presented in Table 4.3. In both types of experiments the indirect self-reporting always yields consistently lower estimates than for direct self-reporting. The estimates based on the ICT experiments seem to largely agree with the urns experiments: almost all of the confidence intervals overlap. According to the table when both types of experiments are compared similar or greater differences between direct and indirect estimates for the urns experiment than for the list experiment are observed, making the original findings appear more conservative in light of this robustness test. Thus, the results from the urns experiment support my main findings from the list experiments.

A study of social desirability bias in authoritarian regimes helps to structure and reconcile many of the diverse arguments and contradictory interpretations about the role of survey research in the electoral politics in those regimes. Even though the majority of the previous research has been focused on understanding the sources of misprediction of electoral outcomes by pollsters, oftentimes due to the inflationary or deflationary effects of the social desirability bias (Bischoping & Schuma 1992; Bodor 2012), this research has taken a different approach by building on the striking observation that the election polls in authoritarian regimes are accurate even though the validity of official results is seriously questioned by the presence of blatant election fraud. In this case, the observed close congruence between the figures of official electoral support and the polling estimates can contribute to well-grounded suspicions concerning the compromised quality of election polls.

Based on anecdotal evidence from election observers and extensive scholarly research on this topic, this section argues that in the 2012 Russian presidential elections the estimates released by Russian national polling organizations contain a substantial degree of inflationary bias with respect to Putin's electoral support, which was persistent throughout the electoral campaign. An important finding here is that the similar level of inflation in turnout for Russia and the US suggests that inflationary mechanism is similar in both countries. Most likely this mechanism has an alternative explanation: if regarding the candidate support respondents might fear repercussions for failing to mention the "right" candidate, in turnout there are no repercussions for suggesting a failure to vote. For those who falsely claim to have voted, the resulting need to name the candidate voted for gives rise to an "information effect" (Bartels 1996) in favor of the leading candidate.

Given the similarity of turnout bias in the two countries, a similar information effect can be expected in Russia which, in this chapter, we have estimated on the basis of a suitable US benchmark at 5 percent. As discussed earlier in the text, regarding support for Putin, the presence of discrepancy between the expected information effect of 5% derived from the U.S. benchmark and observed bias of 20% provided by my empirical data analysis can't be plausibly explained by any other concept than the "spiral of silence". Therefore the estimated inflationary bias once compared with the U.S. benchmark for incumbents provides us with an estimate of about 15%. This estimate is somewhat comparable with the level of election fraud by election administrators. Though being slightly higher than election forensics research suggests, this discrepancy can be explained by the presence of measurement error in the data (Kalinin & Shpilkin 2012). My basic findings are also supported by an alternative urns experiment conducted during the period of the study, reinforcing evidence of the vulnerability of electoral polling in authoritarian regimes.

My analysis demonstrates that the distribution of the social desirability bias is not even across the sample population, yet all social groups demonstrate high and statistically significant levels of social desirability bias in regard to Putin's support with the rich, the young and women demonstrating the highest values of social desirability bias. The social desirability estimates for turnout exhibit somewhat weaker findings: the rich, men and urban residents contribute most to inflated turnout estimates.

Hence, this section by addressing theoretical implications from Noelle-Neumann's seminal work on the "spiral of silence" strongly suggests that when an individual feels unsafe about expressing ideas contrary to official policy or having a fear of isolation, she will most likely hide her private preferences in favor of an incumbent she thinks is most accepted by the general public. My theory suggests that the social desirability bias, inflating the autocrat's support, can be viewed as a valuable resource for the autocratic regime, effectively hiding the vote-rigging needed to convincingly win the election. Once the "spiral of silence" is effectively installed, the general public can be deceived into accepting the election fraud necessary to match the inflationary gap. The observed inflation in election ratings permits election administrators to deliver the results predicted by polls, matching the outcome desired by the autocrat. While this research reveals the presence of significant social desirability bias in the Russian public opinion polls, on a broader scale it poses the problem of the persistence of biased responses and survey errors in authoritarian regimes for a large number of politically sensitive questions.

4.5 Linking Preference Falsification and Election Fraud

4.5.1 Model

The proposed theoretical model is built on three basic assumptions: first, on the day of elections all voters vote in accordance with their private preferences; second, the observed inflation in pre-election ratings originates from preference falsification rather than crude data fabrication conducted by the survey organizations; third, governors do not coordinate their strategies with governors of neighboring regions.

The first assumption implies the presence of voting by secret ballot would be enough to ensure sincere voting similar to secret polling. The second assumption has stronger implications by proposing that pre-election polls are not fabricated by polling organizations to satisfy the governor or the autocrat (see the Theory section for more discussion). The third assumption implies that the governors act independently from each other.

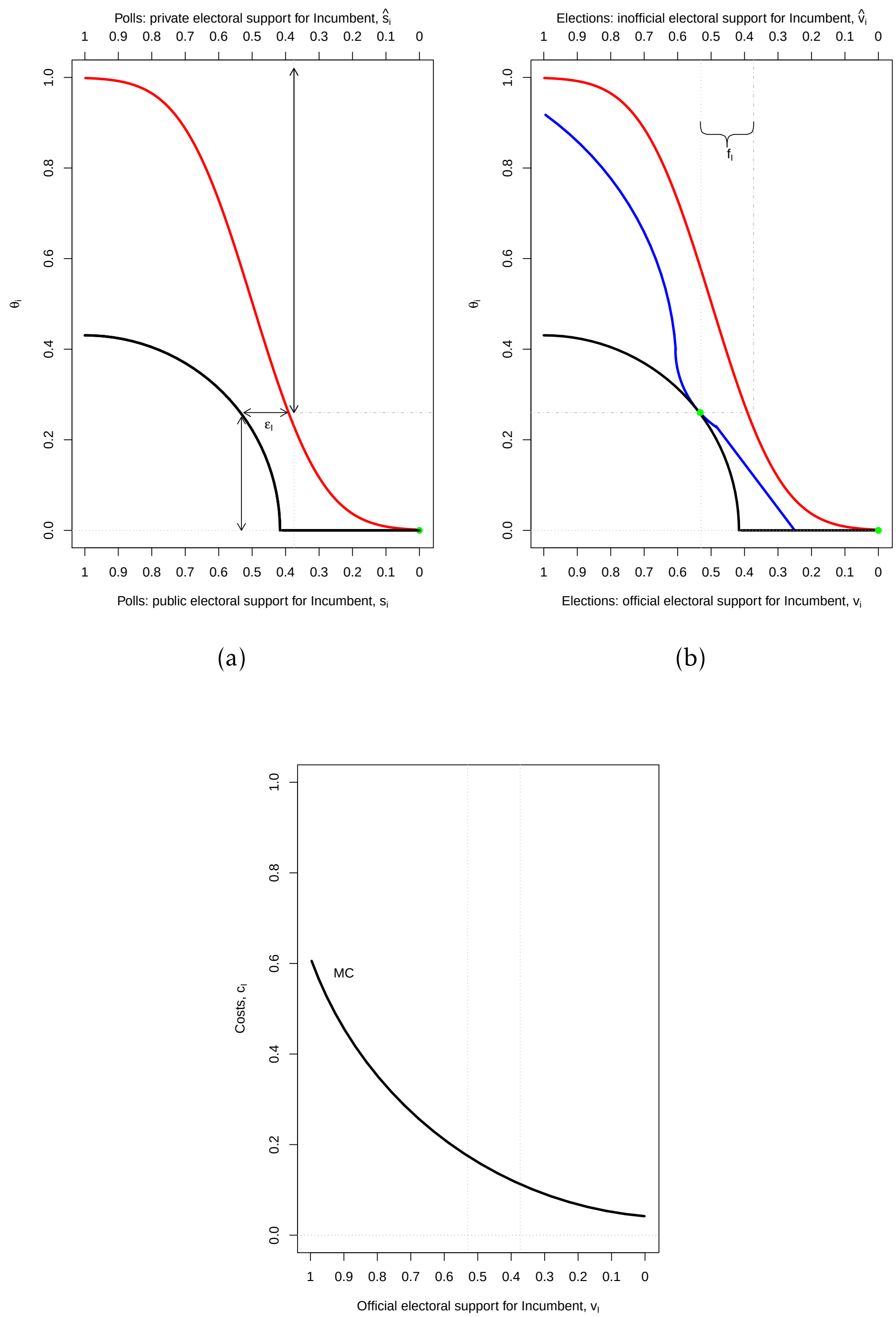
The stylized model is a revised version of Kuran (1987)'s, and will be limited only to analysis of the governor's strategy of selected region to provide a favorable electoral outcome to the autocrat. This game is played in each of the regions. In the game there are N individuals $S = \{1, \ldots, N\}$, from which the respondent i is chosen into the survey. Using the survey, the survey organization is able to measure both types of preferences: individual private and public preferences. It is assumed that two competing candidates enjoy certain level of electoral support. One of the candidates is the autocrat labeled here as incumbent (I) and another one is an opposition candidate (O). For voting for a particular candidate, the voter expects to receive a direct benefit $B_i(\theta_i^{pr})$, where $\theta_i^{pr} \in [0,1]$, i.e. the proportion of those who falsify their preferences. In his decision to reveal the vote he is influenced by the subjectively perceived social pressure, which is a function of the respondent's assessment of pre-electoral vote margin between two major candidates $\hat{s}_I - \hat{s}_O = \lambda_i$. As a result, the respondent's utility function takes the following form: $U_i = B_i - \lambda_i$. The function is single-peaked, meaning there exists a unique policy at which the utility is maximized. Following this, I will subdivide respondents into two groups: *committed respondents*, who are strongly tied to specific candidates and reveal their political preferences in any case ($\lambda_i = 0$), and those who respond to social pressures with a certain degree of preference falsification, i.e. *reluctant respondents* with $\lambda_i \in (0,1)$.

Figure 4.2(a)[1] depicts the incumbent's electoral support of respondents at the pre-election polls. In the Figure, the collective threshold function gives the range of average public support for the incumbent defined by the black curve $\bar{\theta}^{pu}(\hat{s}_I)$: the larger is $\hat{s}_I$ the higher is the probability of $\Phi(\bar{\theta}^{pu})$ of the incumbent's public support by the respondent. The red curve in Figure 4.2(b) $\Phi(\bar{\theta}^{pr})$ denotes the cumulative density function, which measures the share of individuals whose private preferences are to support the incumbent, i.e. $1 - \Phi(\bar{\theta}^{pr})$. As a result, the actual shares of electoral support of the incumbent become: $s_I = 1 - \Phi[\bar{\theta}^{pr}(\hat{s}_I)]$. In Figure 4.2(a) one observes the presence of disequilibrium due to the preference falsification ϵ, since the average public electoral support for the incumbent is 0.52, but the actual share is 0.38, resulting in the proportion of preference falsification in favor of incumbent $\epsilon = 0.14$. The only depicted equilibrium in this graph results from the bandwagon effect at the bottom: if the incumbent is publicly supported by less 40% of respondents, he will end up in losing all the electoral support.

Figure 4.2(b) depicts the electoral stage with the blue curve $f[\Phi(\bar{\theta}^{pr}]$, representing the

[1] In the Figure: θ_i – distribution of individual preferences, $\hat{s}_I$ – private electoral support for incumbent in the polls, s_I – public electoral support for incumbent in the polls, $\hat{v}_I$ – unofficial electoral support for incumbent in the elections, v_I – official electoral support for incumbent in the polls.

Figure 4.2: Preference Falsification and Election Fraud in the Elections



(a) (b)

(c)

manufactured distribution of official "electoral support", which has been shifted in the direction towards the official electoral support by a governor engaging in election fraud. According to the model, the second equilibrium emerges once the amount of election fraud f_I is equal to the magnitude of the preference falsification $f_I = \epsilon_I$ within the margin of error. Hence, Figure 4.2(b) illustrates the presence of two equilibria at the elections: the first equilibrium outcome is most desirable for the autocrat and the governor, since it guarantees the majority of the vote (52%); in contrast, if the election fraud is not enough to win elections (less than 41%), this contributes to a reverse bandwagon process with none of the individuals supporting the incumbent. Thus, if $f_I < \epsilon_I$, then equilibrium with desirable properties for the governor never takes place and he will end up in the inferior Pareto outcome by losing elections. As Simpser's theory suggests, in Figure 4.2(b), the governor will seek to maximize incumbent's vote margin $V_I = v_i - v_o$ and votes v_i by shifting the average public support, defined by the black curve in the upward direction. This is possible through the increase in social pressure λ_i on the respondent exogenously determined by the autocrat and organization of more election fraud f_I. However, the imposed costs for the incumbent defined by $c_I = f_I + \epsilon_I^2$, can serve as an additional check on his actions: greater levels of preference falsification require more vote stealing and higher costs associated with it, thus increasing the marginal cost of each additional vote: $\frac{\Delta c_I}{\Delta V_I}$ $(\frac{\Delta c_I}{\Delta v_I})$ (See Figure 4.2(c)).

Hence, given biased election polls, election fraud f_I is beneficial to the incumbent and the governor, if the following set of necessary conditions is satisfied:

$$\text{Necessary conditions for Fraud:} \begin{cases} \hat{v}_I = \hat{s}_I & (1) \\ \hat{s}_I - s_I = \epsilon_I \quad \text{if} \quad \epsilon_I > 0 & (2) \\ f_I = \epsilon_I \quad \text{if} \quad \epsilon_I > 0 & (3) \end{cases}$$

If any of these necessary conditions is not satisfied than election fraud will never occur. The first condition states that the official vote share v_I is expected to be equal to the incumbent's electoral support in the polls, $\hat{s}_I$. The second condition exposes the magnitude of preference falsification. The third condition implies that the magnitude of election fraud in the election f_I and amount of preference falsification ϵ_I and must be equal. The marginal cost was not included into the set, because in this set it's not necessary, but a sufficient condition for election fraud.

The main implication of this model is related to the expected relationship between preference falsification and election fraud: one would expect that higher levels of preference falsification would require a higher level of election fraud to compensate for the disparity between the pre-election polling results and voting. Thus, the observed inflation in election ratings would encourage the governors to compensate for mismatch by mobilizing their political machines. Hence, my **Hypothesis 4** is that *preference falsification shall positively correlate with the amount of election fraud across Russian regions*. From here I also derive my **Hypothesis 5**, stating that *for the higher magnitude of pre-electoral preference falsification one would expect greater electoral support for the incumbent.*

Since with a decrease in the margin of victory, the marginal cost of election fraud also decreases, the incumbent will be more interested in election fraud than otherwise when the margin of victory is large. Here my **Hypothesis 6** states that *the larger the vote margin is between two major candidates, the weaker the effect of preference falsification on election fraud will be.*

My further analysis of empirical data aims to test the set of conditions for emergence of election fraud and provide empirical evidence in support of the proposed hypotheses.

4.5.2 Data and Measurements

In this empirical part I utilize the official electoral and polling data from the 2012 Russian presidential elections aggregated to the regional level. The polling data was collected by the national polling organization Levada-Center as part of the Omnibus longitudinal study on February 17-20 and February 24-27 of 2012. These both polls are most proximate to the official date of elections, March 4th 2012. For this part of analysis all the electoral data was downloaded from the Russia's Central Election Commission website.

The difficulty of my empirical analysis is related to the hidden nature of election fraud and preference falsification: very often, not only measuring, but even detecting election fraud and preference falsification is problematic. The existing methods of fraud detection combine qualitative, based on the observer reports, and quantitative, based on election forensics, techniques. The field of election forensics includes several methods of election fraud detection, such as digit tests based on the assumption about inability of humans to randomly produce figures in an unbiased way, as well as, parametric models with a set of important distribution assumptions. Last digit tests ("VL", "V05") The last digit test is founded on the assumption that last digits of the vote counts or turnout are uniformly distributed if election fraud does not take place (Beber & Scacco 2008). An application of last digit tests has demonstrated that manipulations of turnout increased over the period 2003 to 2008 in Russia (Mebane & Kalinin 2009a). The last digit approach was further extended by a new test of last digit of percentages, supported by the concept of signaling games. The presence of election fraud becomes a basic signaling mechanism of regional bosses' loyalty and of their ability to control the administrative resources to the Kremlin's benefit (Kalinin & Mebane 2013). If electoral signaling occurs, data manipulation is most likely to take place with rounded percentages of electoral support, which is the easiest and most readily detected way to report basic information to superiors. In such cases, favorable percentages are first sent down from the Kremlin to regional elections commissions, which pass this information to territory-level commissions and, finally, to precincts.

Higher levels of election fraud are therefore associated with a lower mean of last digit of vote counts, and higher proportion of 0s and 5s in the electoral data. This test has been also supported the literature focusing on exploration of spikes in the kernel density estimate of the distribution of both precinct turnout and incumbent's vote shares for values of 60%, 70%, 80%, 90% and 100% Kobak et al. (2016); Mebane and Kalinin (2009a), a pattern initially noticed by Shpilkin and Shulgin (Buzin & Lubarev 2008, 201). Analysis of the last digits of turnout counts in Russia shows an unusually high frequency of zeros and fives Mebane and Kalinin (2009a). Hence, the only plausible explanation for the spiked distributions is a widespread adjustment of turnout to specific rounded figures. In this chapter I will use two digit-based measures of election fraud: the mean of last digit of vote counts ("VL") and the proportion of 0s and 5s ("V05") in a given region (for the precinct-level analysis both measures).

The third measure of election fraud is based on a finite mixture model ("FMM") developed by Mebane (2016), which is partly originated from the Klimek's parametric model (Klimek et al. 2012). Klimek et al. (2012) propose a parametric model quantifying the magnitude of electoral fraud and perform cross-national analysis to test its applicability. The basic assumption of the model is that in fair elections, vote counts and turnout must look approximately Gaussian. In contrast, in rigged elections these distributions are characterized by right-tailed skewness and larger kurtosis. The observation of bimodality in distributions for Uganda and Russia leads the authors to two separate modes of election frauds: ballot switching ("incremental fraud", f_i) and ballot stuffing ("extreme fraud", f_e). Mebane (2016) develops this model further by utilizing a finite mixture likelihood model to estimate three distinct components measured at the precinct level: probabilities of incremental, extreme fraud and no fraud.

Here, a measure of preference falsification based on two pre-election polls is computed using the item count technique (ICT) (Chaudhuri & Christofides 2007; Corstange 2009; Glynn 2013; Green & Kern 2012; Imai 2011; Tsuchiya 2005). The share of respondents privately supporting Putin $\hat{s}_I$ is a standard difference in means estimator of two subsamples (Blair & Imai 2012). The final measure of preference falsification is computed using the formula $\epsilon_I = s_I - \hat{s}_I$, where s_I – is Putin's public vote share computed from the direct question. This preference falsification measure is computed for forty-five Russian regions for which the polling data was available.

Since I am interested the way preference falsification affects election fraud at different levels of the margin of victory, I also construct the "margin of victory" variable based on the electoral data. It is the absolute difference in vote shares between the leading candidate (Vladimir Putin) and the second candidate (Gennadiy Zuganov, the leader of the Communist party).

4.5.3 Results

Before getting to the main analysis, I check to see if the set of conditions derived from the model are met. For this preliminary part I apply a series of paired t-tests to check (a) if a significant difference in the means between direct self-report and official election results is observed; (b) if the share of public electoral support is significantly higher than the share of private electoral support; and (c) if no statistically significant difference is observed between the share of election fraud due to preference falsification and the share of preference falsification. Almost all of the conditions are supported by the data: (a) no statistically significant difference in between the means of public survey preferences and Putin's official election results is observed ($t = 1.03$, $df = 43$, p-value = 0.31); (b) there is a statistically significant difference between public and private electoral preferences for the incumbent ($t = 8.28$, $df = 43$, p-value = 0); and (c) contrary to my expectations, there is a statistically significant difference between election fraud ("FMM" probability measures) and preference falsification with regard to Putin's support($t = 3.88$, $df = 32$, $p = 0.001$). If we compare election fraud ("FMM" proportion of votes that are fraudulent) and preference falsification the difference between both estimates will be even more substantial. The third assumption is the hardest one to meet. It can be violated for the reasons of poor survey quality and measurement errors associated with each estimate.

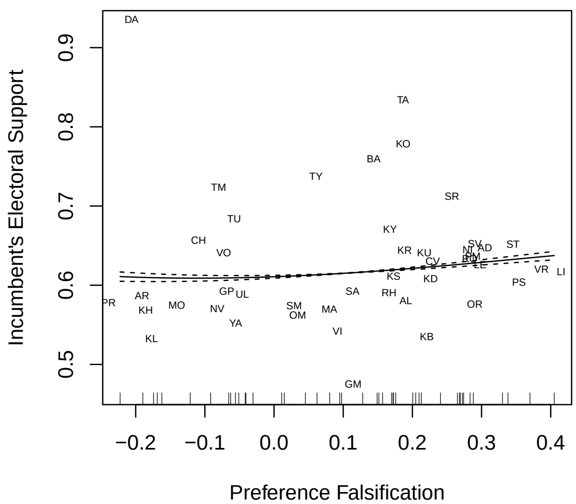
Although the estimates obtained from the regional level data are more "noisy" compared to the national-level estimates, implementation of the nonparametric regression analysis to measure the effects of preference falsification on the incumbent's electoral support in the Russian presidential elections is helpful. In Figure 4.3(a)[2] preference falsification and voting show a statistically significant and positive relationship, which is fully supported by the theory: higher mean values of preference falsification contribute to greater values in Putin's support. Thus, this finding confirms **Hypothesis 5**.

In Figure 4.3(b), containing the last-digit mean of vote counts as a measure of anomaly ("VL"), one observes a statistically significant negative association with the certain degree of non-linearity present: as preference falsification increases, the last digit mean in Putin's vote counts decreases. This pattern suggests the presence of an excessive number of zeros and fives in vote counts, i.e. signaling patterns that shift the regression line downward. The observed convex-shaped curve peaks around the value of preference falsification equal to zero, thus roughly dividing the graph into two regions. The region of preference revelation located on the left-hand side is characterized by a positive association between the two measures; here, as preference revelation decreases, the anomalies in the incumbent's vote counts increase. The region of preference falsification on the right-hand side shows a negative association between both measures; as the preference falsification increases, the quantity of anomalies in incumbent's vote counts decreases.

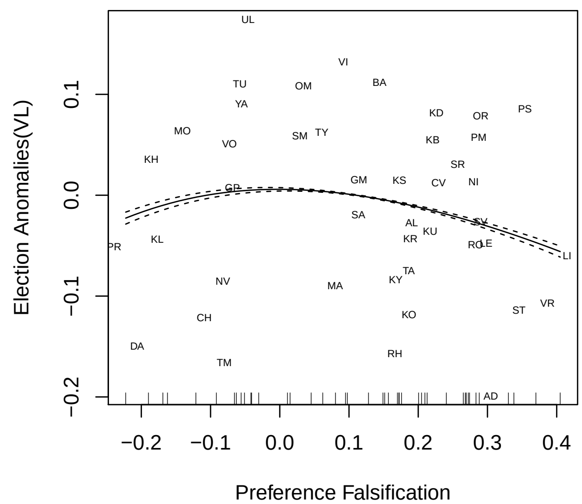
Figure 4.3(c), illustrating whether the proportions of 0s and 5s in incumbent's vote counts are dependent on the level of preference falsification, shows an inverted pattern similar to the nonlinear pattern of "VL". It can be visually divided into the region of preference revelation in the interval $[-0.2;-0.05]$ and the region of preference falsification in the interval $[0.06;-0.4]$. Finally, the finite mixture estimator in Figure 4.3(d) indicates the

[2]"AL" - Altayskiy kray, "AR" - Arkhangel'skaya oblast',"CH" - Chelyabinskaya oblast', "CV" - Chuvashiya Republic, "GM" - Moscow, "GP" - St.Petersburg, "KL" - Kaliningradskaya oblast', "KO" - Kemerovskaya oblast', "KH"- Khabarovskiy kray, "KB" - Kostromskaya oblast', "KR" - Krasnodarskiy kray, "KD" - Krasnoyarskiy kray, "KU" - Kurganskaya oblast', "KS" - Kurskaya oblast', "LE" - Leningradskaya oblast', "LI" - Lipetskaya oblast', "MA" - Magadanskaya oblast', "MO" - Moskovskaya oblast', "NI" - Nizhegorodskaya oblast', "NV" - Novosibirskaya oblast', "OM" - Omskaya oblast', "OR" - Orenburgskaya oblast', "PM" - Permskiy kray, "PR" - Primorskiy kray, "PS" - Pskovskaya oblast', "AD" - Adygeya Republic, "BA" - Bashkortostan Republic, "DA" - Dagestan Republic, "RH"- Khakassiya Republic, "TA" - Tatarstan Republic, "RO" - Rostovskaya oblast', "SA" - Samarskaya oblast', "SR" - Saratovskaya oblast', "SM" - Smolenskaya oblast', "ST" - Stavropol'skiy kray, "SV" - Sverdlovskaya oblast' , "TM" - Tambovskaya oblast', "TU" - Tul'skaya oblast', "TY" - Tyumenskaya oblast', "UL" - Ul'yanovskaya oblast', "VI" - Vladimirskaya oblast', "VO" - Volgogradskaya oblast', "VR" - Voronezhskaya oblast', "YA" - Yaroslavskaya oblast'.

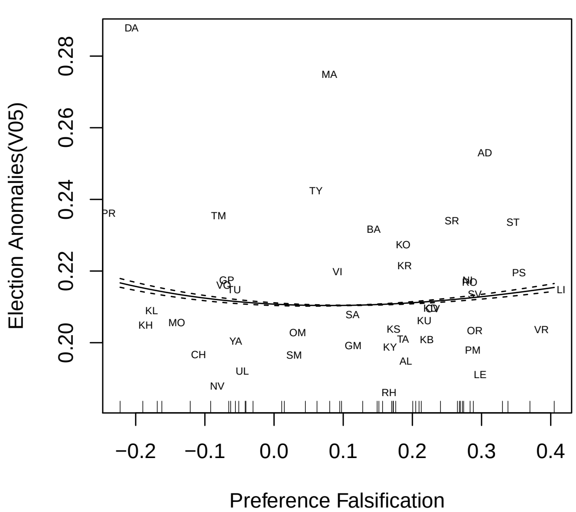
Figure 4.3: Nonparametric Regression: Effect of Preference Falsification on Anomalies in Putin's Electoral Support



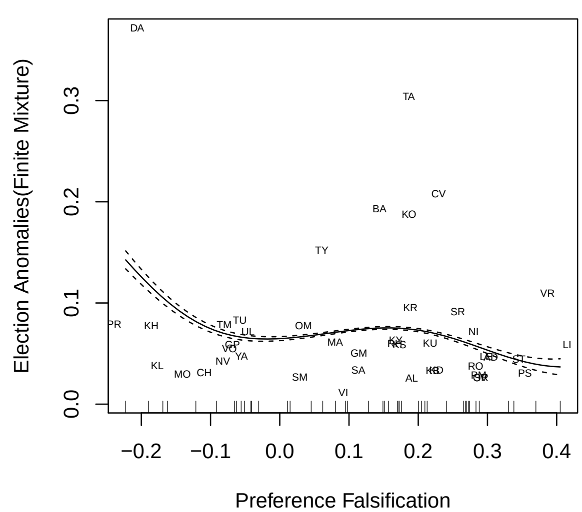
(a)



(b)



(c)



(d)

Table 4.4: Preference Falsification, Election Fraud and Margin of Victory in Russian Elections, 2012 (regions)

	M(01)	M(02)	M(03)
Constant	4.61***	0.17***	−0.11***
	(0.04)	(0.01)	(0.02)
Preference Falsification	-0.26	0.12***	0.3**
	(0.19)	(0.04)	(0.12)
Margin of Victory	−0.25***	0.09***	0.42***
	(0.08)	(0.02)	(0.05)
Preference Falsification X Margin of Victory	0.45	−0.3***	−0.84***
	(0.36)	(0.09)	(0.28)
R^2	0.14	0.34	0.64
Sample Size	44	44	44

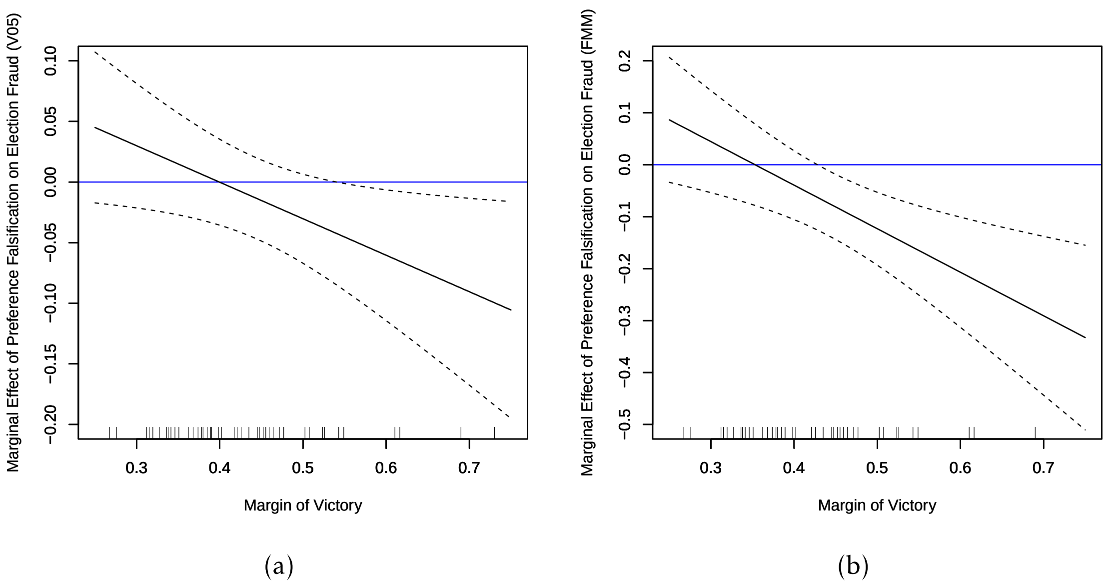
Notes: Robust standard errors in parentheses. Significance levels: *p ≤ 0.1, **p ≤ 0.05, ***p ≤ 0.01. Dependent variables: M(01) – "VL", M(02) – "V05", M(03) – finite mixture estimator.

presence of nonlinearity dividing the graph into three regions: the region of preference revelation $[-0.2; 0]$, weakly defined region of preference falsification $[0; 0.18]$ and ending with the region of preference revelation $[0.2; 0.4]$. In summary, digit tests seem to yield stronger confirmation for my **Hypothesis 4**, compared to the finite mixture estimates. The former test is stronger supported by the signaling theory of election fraud compared to a parametrically estimated measure of election fraud.

For testing my **Hypothesis 6** about whether preference falsification has a weaker effect on election fraud where the margin of victory is larger, I apply to linear regression analysis (See Table 4.4).

While model 1, with the mean of the last digit as dependent variable, yields more mixed findings, the results in models 2 and 3 are in line with my conjectures. The table demonstrates statistically significant main and interaction effects in the predicted direction. The independent effects of preference falsification and margin of victory on election fraud are positive, while their interaction is negative. Further, I visualize the marginal effect of preference falsification on election fraud, conditional on the margin of victory estimated from the electoral data (See Figure 4.4).

Figure 4.4: The Marginal Effect of Preference Falsification Conditional on the Difference of the Margin of Victory Between the Candidates



According to Figure 4.4, as the margin of victory for the party increases, the marginal effect of preference falsification on election fraud decreases. The Figure 4.4(a) shows that the marginal effect of preference falsification on the proportion of 0s and 5s becomes statistically significant when the victory margin is in the range of values between 0.55 and 0.75. Figure 4.4(b) illustrating the marginal effect of preference falsification on finite mixture estimates demonstrates similar a pattern, statistically significant in the range of values between 0.43 and 0.75. Thus, both graphs confirm **Hypothesis 6**, stating that the larger vote margin between the two major candidates contributes to the weaker effect of preference falsification on election fraud ("FMM").

For an additional robustness check, I engage precinct-level data analysis in which each of the measures of anomalies and margin of victory are provided at the precinct-level, and the measures of preference falsification, at the regional level. Based on this data, I estimate linear mixed-effects models ("VL" and "FMM") and generalized linear mixed-effects model ("V05") with a random intercept grouped by the region (See Table

E.5 in Appendix E). The results largely agree with my earlier findings. However, the finite mixture estimate yields the reversed results: preference falsification has a negative effect and the sign of the interaction coefficient between preference falsification and margin of victory is positive. In Appendix E, three additional models were added to the analysis with two extra covariates ("Republics" – indicating if the region belongs to the ethnic region or not, and "Rural" – indicating if the area belongs to rural or urban area) and two extra interaction terms. My findings from three earlier models seem to be in accordance with the results of the extended models. Interestingly, in both "V05" and "FMM" models, the effect of preference falsification on anomalies in ethnic Republics seems to be less acute compared to non-ethnic regions. The effect of preference falsification on anomalies in rural areas (vs urban areas) is strongly positive in the "V05" model but negative in the "FMM" model.

4.5.4 Validation Study: Cross-National Analysis

In order to extend my findings beyond the Russian case, I also apply a statistical analysis of 59 countries with the inclusion of both electoral autocracies and democracies. Unlike the analysis of the Russian data, containing the ICT measure, which enables me to compute the measure of preference falsification, in this section I use a proxy measure of preference falsification – proportion of respondents who refused to respond to polling questions on the electoral support of the winning party. Given the difficulty of directly measuring preference falsification, particularly cross nationally, refusals are an imperfect proxy for the underlying concept. This proxy enables me to measure whether voters hide their private preferences by declining to answer the question on party support, but does not pick up voters' preference misrepresentation. I therefore assume that it captures certain aspects of social desirability bias cross-nationally. The rationale for using this measure is based on the assumption that preference falsification is strongly connected to the item nonresponse: the probability of a respondent misreporting his true preference increases with the degree of sensitivity to the question. For instance, most of the studies point out that income questions typically yield high rates of missing data (Juster & Smith 1997; Moore, Stinson, & Welniak 1999). Specifically, Tourangeau and Yan (2007, 862) argue that the item nonresponse rate for the National Survey of Family Growth for the total household income is the highest compared to other types of sensitive behavior. The authors also conclude that sensitivity to a given question positively correlates with item nonresponse, which can be explained by the fact that sensitivity can be attributed to the content of the question rather than situational factors (Tourangeau & Yan 2007, 862-863). Since the respondent perceives those questions as an invasion of privacy, a truthful answer on a sensitive topic can be seen as inappropriate. Another viable strategy for the respondent would be to decline further participation in the survey or simply to refuse to answer the sensitive question, thus contributing to lower response rates or an increased proportion of missing data for a variable of interest. Since the data on unit nonresponse has been unavailable, I focus my attention on the proportion of respondents who refused to respond to polling questions on the electoral support.

Unlike the "don't know" category, the "refuse to answer" category is more restrictive, excluding those respondents who simply can't make an informed decision. Thus, here I resort to several cross-national election studies carried out in the period between 1990 and 2012, such as Afrobarometer (Rounds 1-4), American National Election Studies (1990-2012), European Social Survey (Rounds 1-6), European Election Study (Trend file), and Latinobarometer (1995-2010). The question of primary interest contains information on the respondent's future or past electoral preferences. By using this data, I obtained two key variables of interest: "Refusals" (the proportion of item nonresponse), and either "Pre-electoral" (referring to whether the survey was conducted before or after the elections) "Margin of Victory"(the vote differential between two leading parties), depending on the timing of the survey. As far as the measure of election fraud is concerned in my cross-national analysis, I apply observer-based measure obtained from the Database of

Political Institutions from the World Bank. According to the released guide, this measure of election fraud "captures extra-constitutional irregularities, which are recorded only if mentioned in sources. 0 reported for countries where, for example, opposition parties are officially and constitutionally banned or where irregularities are not mentioned (although may still exist); "1" when opposition is officially legal but suppressed anyway. Recording is irrespective of whether only opposition claims that fraudulent elections have occurred or whether allegations are backed by independent international observers" (DPI2012 2012, 17). The method's drawback, however, is that there may have been instances of fraud/violence that were not reported, thus resulting in false negatives(DPI2012 2012, 17).

The proposed models include a set of controls related to the leader's success of economic policy, such as lagged GDP growth per capita (variable: "GDP growth (t-1) year"). GDP growth should help the incumbent to increase the credibility of election results, by garnering political support of the population, and to attract more resources necessary to commit election fraud in specific localities (Higashijima 2014). Another measure used as a control variable is the amount of resources at the disposition of the leader expressed in the oil and gas per capita index (Ross 2012). The variable is computed as the product of oil/gas production and oil/gas price divided by total population (in order to solve the scaling problem in the regression analysis the index was also divided by 100). A set of variables measuring political institutions are as follows: the form of the government parliamentary vs. presidential (variable: "Parliamentary"); the sum of the squared seat shares of all parties in the government, showing the amount of representation of the parties in the government (variable "Government"); and a variable measuring the level of democracy (variable: "Polity IV"). The degree of intimidation in a given country is measured by the variable "Violence", which contains a total summed magnitudes of both societal and interstate violence, measured on the scale from 0 to 10 (Major Episodes of Political Violence, MEPV2012 database).

In addition to these two variables I also use the polling data to obtain "Margin of Victory" variable, indicating the vote margin between the two winning parties (a proxy measure of the social pressure). A set of decade interval variables is also included to control for time-specific effects.

Since the observer-based measure is a dummy variable, I apply to estimation of the binary logit model and compute the robust standard errors clustered by countries to solve the problem of heteroscedasticity.

In Table 4.5, models 1-2 present the results of statistical analysis demonstrating that the proportion of refusals is positively related to the probability of election fraud being, statistically significant at $\alpha = 0.05$ level. Thus, my original findings from the Russian data analysis for **Hypothesis 4** are supported by my cross-national data analysis.

The next set of results, utilizing the margin of victory, are shown in the models 3-6 with the main effect of item nonresponse being robust to model specifications. It yields statistically a significant and positive effect on the fraud measure at $\alpha = 0.5$ and $\alpha = 0.1$. For the "Margin of Victory" variable one can observe statistically significant direct effects with a negative sign (models 3 and 6). For model 6, the interaction effect between the proportion of refusals and the margin of victory is negative and statistically significant. Further, I visualize the marginal effect of preference falsification on election fraud, conditional on the margin of victory (See Figure B1). As the margin of victory for the party increases, the marginal effect of refusals on election fraud decreases (the histogram in the Figure shows the distribution of the Margin of Victory variable). As the graph shows, this marginal effect becomes statistically significant when the victory margin is located in the range of values between 0 and 0.60. In other words, as the victory margin becomes larger, the impact of preference falsification on election fraud decreases. Thus, the presented graph supports **Hypothesis 6**, stating that the larger vote margin between the two major candidates or parties contributes to the weaker effect of preference falsification on election fraud.

Table 4.5: Cross-Country Analysis with Margin of Victory (Monitoring Data)

	M(01)	M(02)	M(03)	M(04)	M(05)	M(06)
Constant	$-3.59^{\star\star\star}$	$-3.78^{\star\star\star}$	$-3.43^{\star\star\star}$	1.17	$-4.02^{\star}$	-3.94
	(1.000)	(1.12)	(1.13)	(1.50)	(2.15)	(2.56)
Refusals	$7.32^{\star\star}$	$6.73^{\star}$	2.17	$13.59^{\star\star}$	$81.76^{\star\star\star}$	$92.68^{\star\star\star}$
	(3.53)	(3.6)	(3.75)	(5.5)	(23.19)	(22.34)
Margin of Victory		-0.72	$-5.48^{\star}$	$-5.54^{\star}$	$-12.93^{\star}$	$-11.95^{\star\star\star}$
		(2.09)	(3.26)	(2.86)	(6.86)	(5.33)
Pre-electoral	0.67	0.79	0.8	-0.89	-1.07	-0.99
	(0.82)	(0.84)	(0.87)	(0.97)	(0.87)	(0.99)
Parliamentary				$-10.65^{\star\star\star}$	$-11.8^{\star\star\star}$	$-12.03^{\star\star\star}$
				(0.74)	(1.42)	(1.6)
Oil/Gas(per capita)		-3.92	-3.77	-4.31	$-3.51^{\star}$	$-3.62^{\star}$
		(3.33)	(3.13)	(2.78)	(1.87)	(1.93)
GDP growth(t-1 year)		0.08	$0.09^{\star}$	0.05	0.06	0.06
		(0.07)	(0.05)	(0.04)	(0.04)	(0.04)
Violence		0.25	0.25	0.09	0.01	-0.03
		(0.23)	(0.23)	(0.28)	(0.29)	(0.28)
Government				-0.86		-0.94
				(1.86)		(2.11)
PolityIV				$-0.34^{\star\star}$	0.6	0.93
				(0.16)	(2.22)	(-2.00)
Incumbent's share					4.92	5.86
					(4.01)	(4.32)
Refusals X Margin of Victory			$48.36^{\star}$	-23.99	-84.94	$-113.95^{\star\star\star}$
			(29.19)	(29.96)	(53.44)	(47.86)
PolityIV X Refusals					$-62.69^{\star\star}$	$-73.01^{\star\star\star}$
					(25.9)	(19.2)
PolityIV X Margin of Victory					9.55	$7.61^{\star\star}$
					(7.85)	(4.00)
Refusals X Margin of Vict. X Pol					-33.83	
					(89.27)	
2000s	0.17	0.4	0.43	1.10	1.1	1.2
	(0.75)	(0.89)	(0.9)	(1.37)	(1.43)	(1.6)
R^2	0.04	0.11	0.13	0.4	0.43	0.44
LR χ^2	6.99	16.43	19.87	65.94	72.53	73.71
Number of obs	409	361	361	359	361	359

Notes: For M(01)-M(06) – binary logit models with dependent variable – an observer-based measure of election fraud from the Database of Political Institutions; independent variable of interest – proportion of respondents who refused to respond to polling questions on the electoral support of the winning party. Cluster robust standard errors in parentheses. Significance levels: $^{\star}p \leq 0.1$, $^{\star\star}p \leq 0.05$, $^{\star\star\star}p \leq 0.01$.

Figure 4.5: The Marginal Effect of Preference Falsification Conditional on the Difference of the Margin of Victory Between the Parties

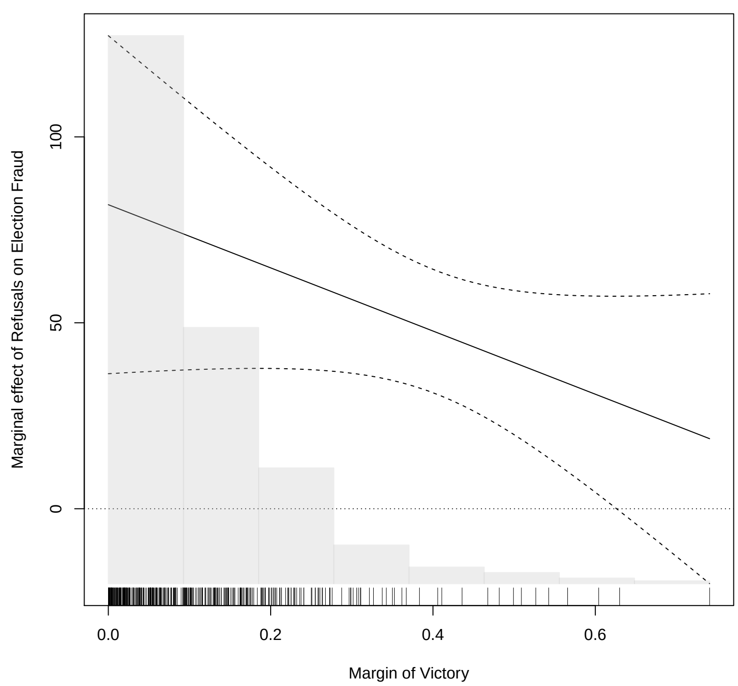
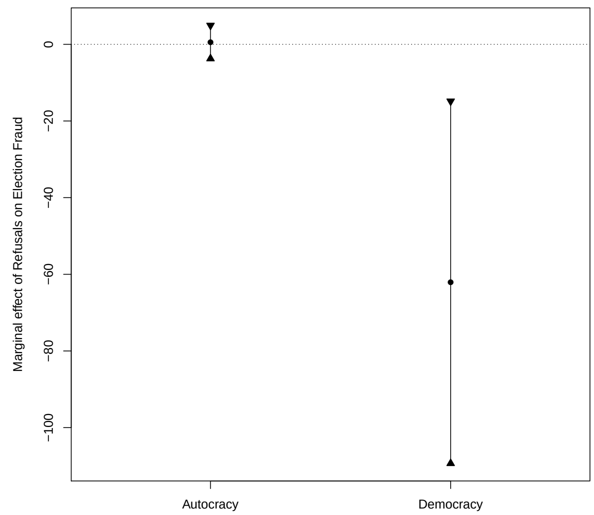
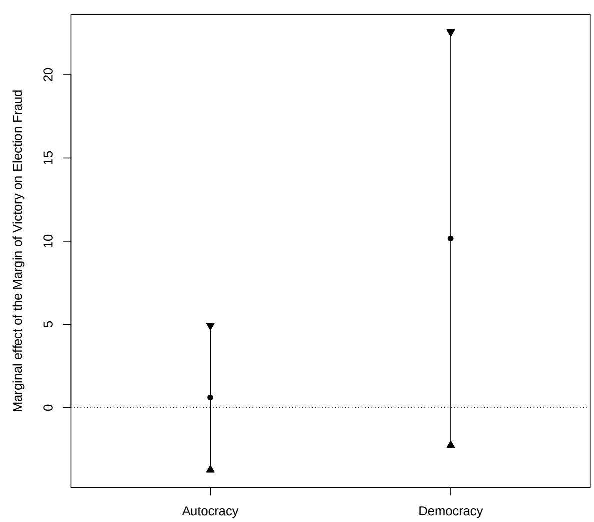


Figure 4.6: Comparing the Effect of Preference Falsification and the Vote Margin on Election Fraud in Democracies and Autocracies



(a)



(b)

The analysis of interaction effect between the Polity score and Refusals shows a statistically significant negative effect (See Figure 4.6 (a,b)). There is a statistically significant difference between electoral autocracies and democracies: compared to democracies, electoral autocracies are characterized with a larger marginal effect of preference falsification on election fraud.

In contrast to this, there is no statistically significant difference between electoral autocracies and democracies in terms of the effect of the margin of victory on election fraud. Moreover, for both electoral autocracies and democracies, a marginal effect of the margin of victory on election fraud is not statistically distinguishable from 0. In other words, according to these findings, social pressure seems to be an insignificant predictor for the level of election fraud conditional on regime type.

4.6 Conclusion

The main objective of this study was, on the one hand, to provide a theoretical framework that links together preference falsification and election fraud in the revised Kuran's model, and, on the other hand, to test whether the implications of the model could be supported in by empirical data analysis.

The importance of pre-election polling in the voter's, autocrat's and survey organization's strategic behavior is truly substantial. According to my findings, the autocrat is strategically interested in boosting preference falsification and organizing the proportionate amount of election fraud in a given country so as to provide himself with the most favorable and, importantly, credible electoral outcome. Undoubtedly, the level of preference falsification exacerbates the role of pre-election polls in guaranteeing the credibility of rigged electoral outcomes for the autocrat. The autocrat's failure to meet this requirement leads to the worse-off outcomes for him, resulting in the Pareto inferior outcomes due to the bandwagon effect.

In this setting the survey organization would be interested in data collection that would permit derivation of "quantifiable" biases and errors, making it possible to extract the genuine information from the biased estimates and provide them to the autocrat. Finally, organization of election fraud in the Russian setting is entrusted to the heads of the regional governments engaging in competitive falsification to show loyalty and extract certain benefits from the center.

My empirical findings derived from the analysis of the Russian electoral data and cross-national analysis strongly support the theoretical implications of the model. First, analysis of both datasets shows that preference falsification is indeed positively related to the amount of election fraud in a given country. Second, the hypothesis that the incumbent earns a larger vote share by increasing the level of preference falsification is confirmed. Third, my hypothesis about the presence of a moderation effect of the margin of victory is confirmed: indeed, the marginal effect of preference falsification on election fraud becomes weaker with an increase of the margin of victory between two leading candidates.

While these findings look promising, there are several important limitations to this research. First, analysis of the Russian data was performed on a sample of the regions, which might be different from those left outside of the analysis. Second, the presence of nonlinear patterns in my non-parametric analysis provided me with mixed evidence in favor of the main hypothesis. Third, the auxiliary cross-national data analysis on the part of the preference falsification variable was entirely based on academic surveys rather than pre-election polls. Even though these limitations are substantial for our consideration, the successful generalization of my findings makes them applicable to a broad set of electoral autocracies. This research helps to come closer to a better understanding of the mechanism by which the survey polls can be important in different political settings, and sets a new research agenda for the fields of political science and survey methodology.

CHAPTER V

Conclusion

This dissertation sought to explore the methodological and theoretical aspects of election forensics research. It focused on a balanced discussion of various forensics tests, methods and web applications needed for detection and measurement of electoral anomalies in the data. It also attempted to contribute to the field of election forensics by proposing two innovative theories aimed to unravel the mechanisms behind certain anomalous data patterns and test them using the Russian as well as cross-national data analysis.

Chapter 2 of this dissertation was devoted to the exploration of election forensics methodology and validation of the finite mixture model. From this Chapter we learnt that even though none of the election forensics statistics provide definitive proof of fraud, the combination of electoral and auxiliary data enables us to strengthen our conjectures. This research was specifically aimed at validating finite mixture model of election fraud using auxiliary data from election observation and different voting modes. The new measure confirms our expectations about vote rigging taking place in the polling stations with ballot boxes rather than KOIBs/KEGs, and without well-trained observers rather than with them. Moreover, based on the presented evidence, it can be also concluded that several traditional election forensics indicators can serve as relatively good predictors for these new measures. There is a relatively strong correlation between various clusters measured with the help of different forensics indicators, which is indicative of consistency between various measures of election fraud and across the Russian elections.

Chapter 3 offered a theoretical perspective on how election fraud can be closely associated with the loyalty of subnational agents. My analysis suggests that institutional change over time associated with Putin's recentralization policies in the 2000s also impacted the structure of election frauds in Russia. In terms of the game model, the value of the parameter d, the value to the Leader of replacing a disloyal governor, greatly increased. As recentralization gained hold, the threat associated with transfers to regions often decreased—the threat of regional secession disappeared—so that the long-run returns associated with transfers likely often increased: b was less often negative or at least often less negative. These changes changed the strategies governors and the Kremlin found optimal, leading to the situations seen in 2004 and 2008, where election frauds are easy to detect because governors use them to send signals to the Kremlin. As it was shown, in Russia, the occurrence of zeros or fives as the last digit in turnout and vote percentages is connected to an extensive signaling structure wherein election frauds are connected to postelection rewards and punishments

My game-theoretical propositions in Chapter 3 was also subjected to cross-national data analysis by classifying equilibria profiles from the signaling game across multiple political regimes. The empirical analysis based on unique original datasets helps us to draw two important conclusions. First, specific signaling patterns seem to be prevalent in cross-national data as well as in the Russian data: an abundance of zeros and fives contributes to growing financial decentralization, i.e. leading to more resources concentrated in the regions. Second, in accordance with my theoretical expectations, autocracies are characterized by greater signaling patterns than democracies. Moreover, counter to my theoretic expectations, the signaling patterns seem to be prevalent in the unitary states compared to the federal ones. Although the implications from the formal model are suggestive of this, intuitively it seems plausible that the unitary states are expected to show greater signaling patterns compared to the federal ones, because of the stronger institutional loyalties and larger consolidation of resources in the center. The observed complexity in interpretation of results may be also due to classification errors and subsequent misattribution of equilibria profiles to specific regimes.

The main objective of Chapter 4 was, on the one hand, to provide a theoretical framework that links together preference falsification and election fraud in the revised Kuran's model, and, on the other hand, to test whether the implications of the model could be supported by empirical data analysis. According to my theory, the importance of pre-election polling in the voter's, autocrat's and survey organization's strategic behavior is truly substantial. Empirical findings illustrate that the autocrat is strategically interested in boosting preference falsification and organizing the proportionate amount of election fraud in a given country so as to provide himself with the most favorable and, importantly, credible electoral outcome. Undoubtedly, the level of preference falsification exacerbates the role of pre-election polls in guaranteeing the credibility of rigged electoral outcomes for the autocrat. The autocrat's failure to meet this requirement leads to the worse-off outcomes for him, resulting in the Pareto inferior outcomes due to the bandwagon effect. In this setting the survey organization would be interested in data collection that would permit derivation of "quantifiable" biases and errors, making it possible to extract the genuine information from the biased estimates and provide them to the autocrat. Finally, organization of election fraud in the Russian setting is entrusted to the heads of the regional governments engaging in competitive falsification to show loyalty and extract certain benefits from the center. My empirical findings derived from the analysis of the Russian electoral data and cross-national analysis strongly support the theoretical implications of the model. First, analysis of both datasets shows that preference falsification indeed positively affects the amount of election fraud in a given country. Second, the hypothesis that the incumbent earns a larger vote share by increasing the level of preference falsification is confirmed. Third, my hypothesis about the presence of a moderation effect of the margin of victory is confirmed: indeed, the marginal effect of preference falsification on election fraud becomes weaker with an increase of the margin of victory between two leading candidates.

What comes next? The finite mixture estimator, developed by Mebane (2016), so far, seems to be the most promising tool in election forensics research, especially if combined with other methods. Implementation of all these methods via the web-application "Election Forensics Toolkit" makes election forensics methodology technically accessible to many interest individuals and organizations. Its further development will harness these social scientific efforts to create innovative resources for policymakers, practitioners, and scholars who study and evaluate election outcomes enabling them to evaluate better the integrity of election returns. As the Toolkit develops into the Portal we will build an international community of people with different backgrounds, sharing similar research interests, and having access to different data sources and methodologies. It will serve as an information hub for researchers, practitioners, and observers by providing a convenient interface for data collection and data sharing, as well as quick and easy access to election forensics results presented in graphs, tables, dynamic maps. It will help these professionals to stay interconnected and informed about the most up-to-date techniques of election forensics analysis. Specifically, it will help to reach the following goals: a) make election forensics results quickly and easily accessible for on-the-ground monitoring of elections by domestic and foreign observers, as well as ordinary citizens; b) help to make most up-to-date election forensics methods easily accessible for data analysis anywhere in the world where internet connection is provided; c) create high-quality visuals (maps, graphs, tables) for presentations to the wider audiences, experts and journalists; d) develop dynamic maps designed to present geo-referenced election forensics results in a user-friendly format; e) create an on-time monitoring news system of election fraud around the world; f) integrate the website with the parallel vote tabulation (PVT), which can be used by different observer missions around the globe; g) accumulate, store, and disseminate data and election forensics results among the interested audiences; h) build an international community of people interested in election forensics methodology and data analysis.

Unfortunately, development of election forensics methodology can also lead to elevated risks and challenges of autocratic adaptation, expressed in such data fabrication that would make it insensitive to contemporary election forensics methods and techniques. Being explored by Sjoberg (2014), this phenomenon was demonstrated in the dissertation's opening paragraph related to the past Russian Duma elections. The interests of resource-rich autocrats to organize election fraud specifically designed to remain undetectable by election forensics methods, is one of the major concerns that needs to be fully addressed in the future. In this sense, the methodological transparency of election forensics, which is the virtue of the field, can pose the long-term challenges associated with autocratic adaptation and data resistance to "super-frauds". In the future, I hope to explore this issue in greater depth, proposing theory and describing the mechanisms of autocratic adaptation.

APPENDICES

APPENDIX A

Supplementary Information for Chapter 1

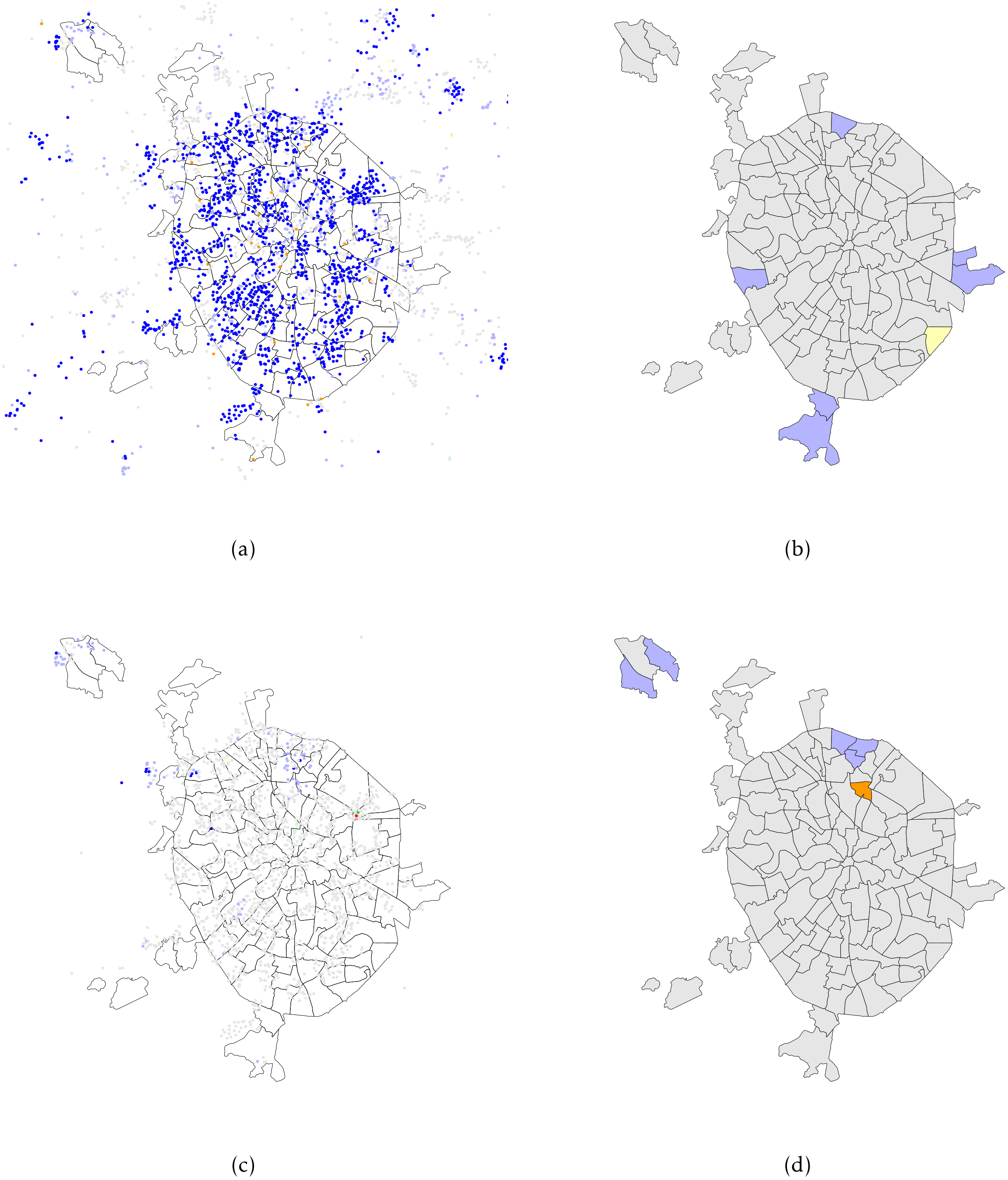
Figure A.1: KEGs vs. KOIBS

(a)

(b)

Notes: Images are taken from *http://www.cikrf.ru*

Figure A.2: Cluster and Outlier Analysis for Moscow f_i



Notes: Overall fraud probability averages are in parentheses. (a,b) – 2012 (0.09); (c,d) 2011 (0.13).

Table A.1: Number of Territories and Precincts in the Anomalous Clusters (red spots), by Region

Region	Presidential Election				Parliamentary Election			
	Precincts		Territories		Precincts		Territories	
	f_e	f_i	f_e	f_i	f_e	f_i	f_e	f_i
Amurskaya oblast’						3		
Belgorodskaya oblast’	4	171		2	17	280		14
Bryanskaya oblast’		7				11		
Chechnya Republic	95	154	12	14			12	14
Chelyabinskaya oblast’					9	38		
Chukotskiy autonomous okrug		1						
Chuvashiya Republic	8	306		9	2	24		2
Gorod Moskva						3		
Irkutskaya oblast’						3		
Kabardino-Balkariya Republic					162	179		8
Kaluzhskaya oblast’		17				53		3
Karachaevo-Cherkessiya Republic		111		9	23	133		9
Kemerovskaya oblast’	2	189		5				
Khabarovskiy kray		1						
Khanty-Mansiysk autonomous okrug		13		1				
Kirovskaya oblast’						3		
Kostromskaya oblast’						1		
Krasnodarskiy kray	3	63			36	377		13
Krasnoyarskiy kray						2		1
Kurganskaya oblast’		1				6		
Kurskaya oblast’		10				10		
Lipetskaya oblast’		2						
Moskovskaya oblast’	1							
Nizhegorodskaya oblast’		20		1	1	60		2
Novosibirskaya oblast’		4				58		
Omskaya oblast’		34			1	60		1
Orenburgskaya oblast’		1				8		1
Orlovskaya oblast’		5			2	27		
Penzenskaya oblast’		20		4				6
Primorskij kraj		7						
Adygeya Republic						1		1

Notes: Only those regions were selected in which at least one cluster was detected.

Table A.1 (Continued): Number of Territories and Precincts in the Anomalous Clusters, by Region

Region	Presidential Election				Parliamentary Election			
	Precincts		Territories		Precincts		Territories	
	f_e	f_i	f_e	f_i	f_e	f_i	f_e	f_i
Altay Republic		3		1				2
Bashkortostan Republic	3	404		17				8
Buryatiya Republic		6				6		
Dagestan Republic		453	1	39	14	403	1	27
Ingushetiya Republic		54		3		39		2
Kalmykiya Republic		1						
Khakassiya Republic				1		6		
Komi Republic		1			1	84		1
Mariy El Republic		9		2				3
Mordoviya Republic	5	181		14				20
Sakha Republic		82		10	1	54		1
Severnaya Osetiya Republic	2	78		3	9	200		8
Tatarstan Republic	1	560		41	3	658		34
Tyva Republic		86		17		15		5
Rostovskaya oblast’		2				32		
Ryazanskaya oblast’		3				7		
Samarskaya oblast’		4						2
Saratovskaya oblast’		51						
Stavropol’skiy kray		9			1	5		1
Tambovskaya oblast’		1			2	67		
Tomskaya oblast’						1		
Tul’skaya oblast’		8						
Tyumenskaya oblast’		69						
Udmurtiya Republic		4		1		1		
Ul’yanovskaya oblast’		29		2				6
Volgogradskaya oblast’		16				4		
Voronezhskaya oblast’		59			9	210		14
Yamalo-Nenetskiy autonomous okrug		70		8		104		5
Yaroslavskaya oblast’		2				2		
Zabaykal’skiy kray						2		

APPENDIX B

Supplementary Information for Chapter 2: Formal Model

Table B.1: Game in Multiagent Strategic Normal Form

P_2

		P_1	$\neg P_1$
F_1	F_2	$-w-p$, $v-p+(1-\lambda)d$	$-w+t[1+b(1-\lambda)]$, $v+t(\lambda b-1)$
F_1	$\neg F_2$	$-\lambda w-p$, $\lambda w-p+(1-\lambda)d$	$-p(1-\lambda)-\lambda(w-t)$, $\lambda[(b-1)t+v]+(1-\lambda)(d-p)$
$\neg F_1$	F_2	$-(1-\lambda)w-p$, $-p+(1-\lambda)(v+d)$	$-\lambda p+(1-\lambda)[(b+1)t-w]$, $-\lambda p+(1-\lambda)(v-t)$
$\neg F_1$	$\neg F_2$	$-p$, $-p+(1-\lambda)d$	$-p$, $-p+(1-\lambda)d$

$\neg P_2$

		P_1	$\neg P_1$
F_1	F_2	$-w-p$, $v-p+(1-\lambda)d$	$-w+t[1+b(1-\lambda)]$, $v-t(\lambda b-1)$
F_1	$\neg F_2$	$-\lambda(w+p)+(1-\lambda)(b+1)t$, $\lambda(v-p)-(1-\lambda)t$	$-\lambda w+t[1+(1-\lambda)b]$, $\lambda v+(\lambda b-1)t$
$\neg F_1$	F_2	$-\lambda(w+p)+(1-\lambda)t$, $\lambda(b-1)t+(1-\lambda)(v-p+d)$	$t[1+(1-\lambda)b]-(1-\lambda)w$, $(1-\lambda)v+(\lambda b-1)t$
$\neg F_1$	$\neg F_2$	$-p$, $\lambda(b-1)t-(1-\lambda)t$	$t[1+(1-\lambda)b]$, $(\lambda b-1)t$

Table B.2: Payoffs for Strategy Profiles

label	profile	governor's payoff	Leader's payoff
I*	$(F_1, F_2, \neg P_1, \neg P_2)$	$-w + t[1 + (1-\lambda)b]$	$v + (\lambda b - 1)t$
II*	$(F_1, \neg F_2, \neg P_1, P_2)$	$-p(1-\lambda) - \lambda(w-t)$	$\lambda[(b-1)t + v] + (1-\lambda)(d-p)$
III*	$(F_1, F_2, \neg P_1, P_2)$	$-w + t[1 + b(1-\lambda)]$	$v + t(\lambda b - 1)$
IV*	$(F_1, \neg F_2, P_1, P_2)$	$-\lambda w - p$	$\lambda v - p + (1-\lambda)d$
V*	$(F_1, \neg F_2, P_1, \neg P_2)$	$-\lambda(w-p) + (1-\lambda)(b+1)t$	$\lambda(v-p) + (1-\lambda)(-t)$
VI*	$(F_1, \neg F_2, \neg P_1, \neg P_2)$	$-\lambda w + t[1 + (1-\lambda)b]$	$\lambda v + (\lambda b - 1)t$
VII*	$(\neg F_1, \neg F_2, \neg P_1, \neg P_2)$	$t[1 + (1-\lambda)b]$	$(\lambda b - 1)t$
VIII*	$(\neg F_1, \neg F_2, P_1, P_2)$	$-p$	$-p + (1-\lambda)d$
IX*	(F_1, F_2, P_1, P_2)	$-w - p$	$v - p + (1-\lambda)d$
X*	$(\neg F_1, F_2, P_1, P_2)$	$-(1-\lambda)w - p$	$-p + (1-\lambda)(v+d)$
XI*	$(\neg F_1, F_2, \neg P_1, P_2)$	$-\lambda p + (1-\lambda)[(b+1)t - w]$	$-\lambda p + (1-\lambda)(v-t)$
XII*	$(\neg F_1, \neg F_2, \neg P_1, P_2)$	$-p$	$-p + (1-\lambda)d$
XIII*	$(F_1, F_2, P_1, \neg P_2)$	$-w - p$	$v - p + (1-\lambda)d$
XIV*	$(\neg F_1, F_2, P_1, \neg P_2)$	$-\lambda(w+p) + (1-\lambda)t$	$\lambda(b-1)t + (1-\lambda)(v-p+d)$
XV*	$(\neg F_1, \neg F_2, P_1, \neg P_2)$	$-p$	$\lambda(b-1)t + (1-\lambda)(-t)$
XVI*	$(\neg F_1, F_2, \neg P_1, \neg P_2)$	$t[1 + (1-\lambda)b] - (1-\lambda)w$	$(1-\lambda)v + (\lambda b - 1)t$

Table B.3: Some Equilibrium Tests

label	profile	equilibrium conditions
I*	$(F_1, F_2, \neg P_1, \neg P_2)$:	$\lambda = 1 \cap w = 0$
II*	$(F_1, \neg F_2, \neg P_1, P_2)$:	$\lambda = 0 \cap \frac{-p-t}{t} \geq b$, $\lambda = 1 \cap \frac{t+p}{t} \geq b \geq \frac{t-p-v}{t}$
III*	$(F_1, F_2, \neg P_1, P_2)$:	complicated (see Table B.4)
IV*	$(F_1, \neg F_2, P_1, P_2)$:	never
V*	$(F_1, \neg F_2, P_1, \neg P_2)$:	$\lambda = 0 \cap p \geq -(1+b)t$, $\lambda = 1 \cap b \leq 0 \cap (1-b)t \geq p \geq t \cap 2p \geq w$
VI*	$(F_1, \neg F_2, \neg P_1, \neg P_2)$:	$\lambda = 1 \cap w = 0 \cap t \geq p \cap b \geq 0$
VII*	$(\neg F_1, \neg F_2, \neg P_1, \neg P_2)$:	never
VIII*	$(\neg F_1, \neg F_2, P_1, P_2)$:	never
IX*	(F_1, F_2, P_1, P_2):	$\lambda < 1 \cap w = 0 \cap \frac{-(p+t)}{(1-\lambda)t} \geq b$
X*	$(\neg F_1, F_2, P_1, P_2)$:	never
XI*	$(\neg F_1, F_2, \neg P_1, P_2)$:	$\lambda = 0 \cap w = 0 \cap b \geq \frac{w-p-t}{t}$
XII*	$(\neg F_1, \neg F_2, \neg P_1, P_2)$:	$w \geq p + t \cap t + d \geq p + v$
XIII*	$(F_1, F_2, P_1, \neg P_2)$:	never
XIV*	$(\neg F_1, F_2, P_1, \neg P_2)$:	never
XV*	$(\neg F_1, \neg F_2, P_1, \neg P_2)$:	$\frac{t+p}{w+t+p} \leq \lambda < 1 \cap \frac{-(p+t)}{(1-\lambda)t} \geq b \geq \frac{v+t-p}{t}$
XVI*	$(\neg F_1, F_2, \neg P_1, \neg P_2)$:	$\lambda = 0 \cap w = 0 \cap b \geq 0 \cap p \geq d + t$

Table B.4: Equilibrium Tests for Profile III*

	profile	governor's payoff	Leader's payoff
III*	$(F_1, F_2, \neg P_1, P_2)$	$-w + t[1 + b(1-\lambda)]$	$v + t(\lambda b - 1)$

conditions:

$\lambda = 0 \Rrightarrow t(b+1) \geq w - p \cap v + d \geq t - p \cap p - t \geq d$

$\lambda = 1 \Rrightarrow t \geq w - p \cap t(b-1) \geq -p$

$0 < \lambda < 1 \Rrightarrow t + p \geq w \cap t(b+1) + p \geq w \cap v + t(b-1) + p \geq 0 \cap v + d + p \geq t$

$\cap$t(b+1)+p$\geq \lambda bt \geq (1-\lambda)d + t - p$

$$\Rightarrow \begin{cases} & \text{if b<0} \\ \lambda \geq 1+(t-p)/d, & \\ & \text{if b>0} \end{cases}$$

$b < 0$: $\quad 1 + \frac{t+p}{bt} = 0$ if $b = -\frac{t+p}{t}$, $\quad 1 - \frac{t(b-1)+p}{bt+d} = 1$ if $b = \frac{t-p}{t}$

$b > 0$: $\quad \lim_{t\to\infty}(1+ \frac{t+p}{bt}$=1+ $\frac{1}{b}$, $\quad \lim_{t\to\infty}$ (1- $\frac{t(b-1)+p}{bt+d}$= $\frac{1}{b}$

APPENDIX C

Supplementary Information for Chapter 2: Russian Analysis

Table C.1: Distribution of Last Digits for Precinct Vote Totals in Russian Elections 2003–2012

	Year											
	2003		2004		2007		2008		2011		2012	
Digit	Repub.	Oblast	Repub.	Oblast	Repub.	Oblast	Repub.	Oblast	Repub.	Oblast	Repub.	Oblast
0	**6.2**	**3.0**	**9.9**	**4.7**	**10.5**	**7.7**	**15.4**	**10.5**	**11.4**	**5.6**	**8.0**	**2.9**
1	-2.0	0.1	-1.8	1.3	-0.8	0.1	-1.4	-0.7	-2.9	-1.0	-2.3	1.0
2	-0.6	-0.4	1.1	0.5	-1.3	1.7	-2.1	-0.2	0.9	-2.7	0.2	-1.1
3	-1.2	-1.0	-1.8	-0.7	-0.6	-1.4	-1.9	-2.1	-0.5	-1.3	-2.6	-2.2
4	0.7	-0.3	-3.3	-0.8	-3.4	-1.0	-3.7	-1.3	-3.8	1.2	-0.1	-0.8
5	**3.1**	**0.9**	**2.1**	**3.3**	**2.1**	**-0.2**	**2.7**	**0.8**	**1.3**	**0.4**	**1.3**	**1.4**
6	-1.8	-0.9	-0.1	0.0	-2.8	-1.8	-1.3	-1.1	-2.9	0.6	-1.8	0.1
7	-0.2	0.9	-2.0	-2.2	-1.1	-0.9	-3.1	0.0	-1.6	0.2	-0.9	1.2
8	-0.7	-1.5	-0.7	-2.1	-0.3	-0.8	-1.4	-1.0	-0.3	-1.1	-1.5	-1.0
9	-3.5	-0.8	-3.4	-4.0	-2.3	-3.5	-3.2	-4.9	-1.5	-1.8	-0.3	-1.4
χ^2_L	69.9	15.4	137.2	60.9	144.2	82.0	292.2	143.0	169.9	47.33	84.1	22.3
n	17,008	77,305	17,600	77,824	17,875	77,928	17,865	78,383	17,732	77,435	17,729	77,685

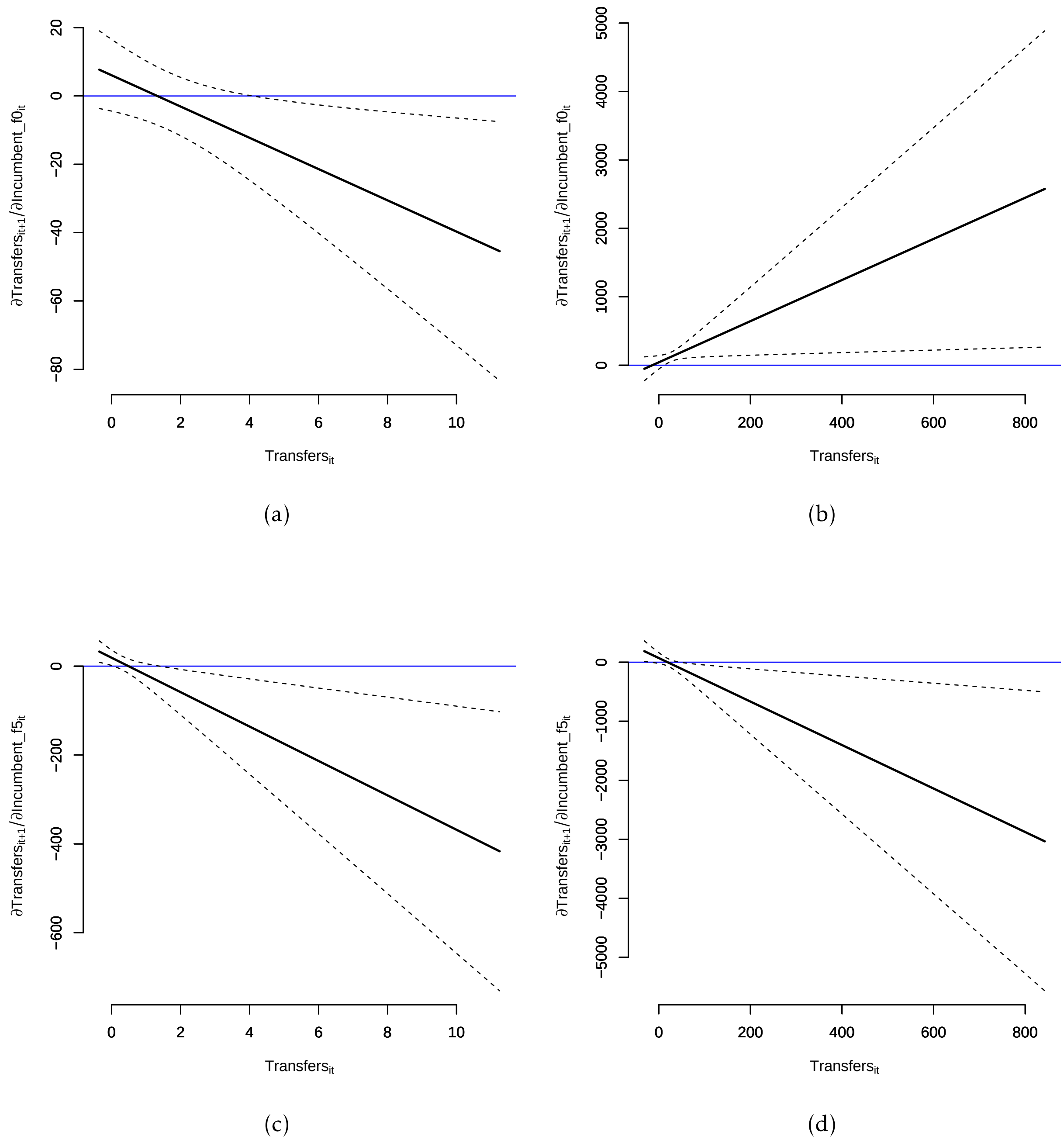
Notes: Entries for each digit show signed square roots of chi-squared statistics implied by the null hypothesis that the total number of votes cast at each UIK (polling station) have uniformly distributed last digits. The χ^2_L statistics show the overall Pearson chi-squared statistic (9 degrees of freedom). n shows the number of UIKs.

Table C.2: Panel Data Analysis with the First-Difference Estimator, NLS

	M(01)	M(02)	M(03)	M(04)	M(05)	M(06)
Constant b_0	1.166***	-0.242	1.006***	-0.319*	4.149***	-0.086
	(0.113)	(0.16)	(0.227)	(0.135)	(0.048)	(0.08)
Incumbent c_2	0.98	0.322**	0.635	0.361*	-0.298	0.109
	(0.763)	(0.112)	(0.892)	(0.158)	(0.483)	(0.16)
Turnout c_3	-2.634	-1.207***	-2.002	-1.611***	-0.203	-0.016
	(2.258)	(0.278)	(2.344)	(0.285)	(0.42)	(0.117)
Constant a_0	5.504	0.61	4.116	0.547	-51.7***	-1.301*
	(4.142)	(0.771)	(2.662)	(0.574)	(14.67)	(0.512)
Transfers a_1	14.797	0.448*	11.589	0.532*	11.599***	3.209***
	(10.427)	(0.201)	(7.303)	(0.226)	(3.303)	(0.865)
fraudT0 f_0	-0.787	0.041	-1.294**	-0.059	-0.696**	-0.06
	(0.526)	(0.085)	(0.438)	(0.095)	(0.248)	(0.081)
fraudT5 f_5	1.158	-0.203	0.576	-0.172	0.3	-0.179*
	(0.765)	(0.087)	(0.891)	(0.109)	(0.354)	(0.086)
fraudI0 f_0	0.36	-0.04	0.431	-0.005	0.049	0.035
	(0.197)	(0.046)	(0.229)	(0.068)	(0.228)	(0.069)
fraudI5 f_5	-0.396	0.018	0.085	0.028	0.101	-0.027
	(0.705)	(0.096)	(0.928)	(0.107)	(0.4)	(0.094)
$\hat{\sigma}$	0.761	0.118	0.758	0.114	0.253	0.07
N	83	83	83	83	80	80

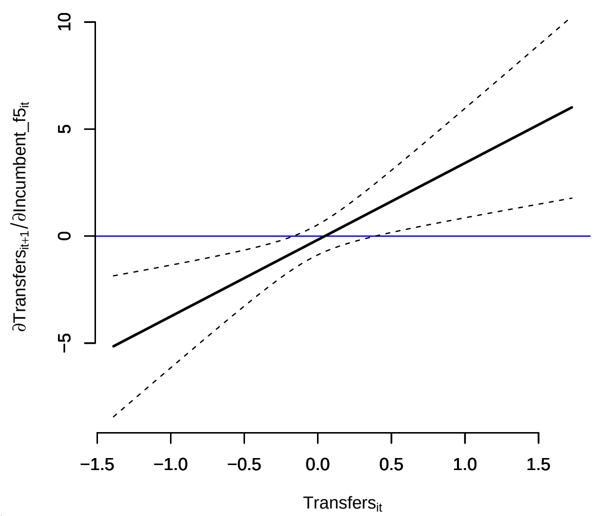
Notes: Robust standard errors in parentheses. Significance levels: *p ≤ 0.05, **p ≤ 0.01, ***p ≤ 0.001. Listed models: a) the first-difference estimator for 1996(first round) and 2000 with logged transfers per capita M(01) and M(02) with the share of central transfers in the regional budget as dependent variables; b) the first-difference estimator for 1996(second round) and 2000 with the logged transfers per capita M(03) and share of central transfers in the regional budget M(04) as dependent variables; c) the first-difference estimator for 2004 and 2008 with logged transfers per capita M(05) and the share of central transfers in the regional budget M(06) as dependent variables.
Nonlinear least squares estimates for all the models:
[a] $\Delta\mathtt{Transfers}_{it} = b_0 + c_1\Delta\mathtt{Incumbent}_{it} + c_2\Delta\mathtt{Turnout}_{it} + f_0\Delta\mathtt{fraudT0}_{it} + f_5\Delta\mathtt{fraudT5}_{it} + f_0\Delta\mathtt{fraudI0}_{it} + f_5\Delta\mathtt{fraudI5}_{it} + \lambda_{it} + \lambda_{it}\cdot(f_0\Delta\mathtt{fraudT0}_{it} + f_5\Delta\mathtt{fraudT5}_{it} + f_0\Delta\mathtt{fraudI0}_{it} + f_5\Delta\mathtt{fraudI5}_{it})$,
$\lambda_{it} = \dfrac{1}{1+\exp\{-(a_0 + a_1\Delta\mathtt{Transfers}_{it-})\}}$.

Figure C.1: The Marginal Effects of Election Fraud in Incumbent's Percentage on Post-electoral Transfers)

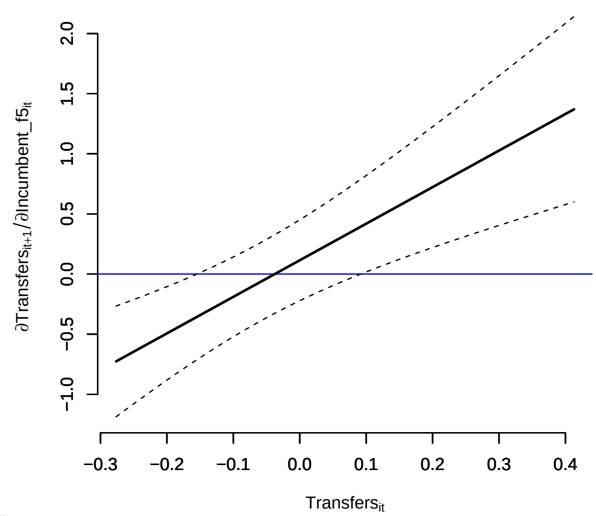


Notes: Estimated marginal effects for the models in Table 3.4: (a)M(01), (b)M(05), (c)M(03), (d)M(05), (e)M(02), (f)M(06). Figures show the marginal effect of election fraud on post-electoral transfers conditional on pre-electoral transfers.

Figure C.1 (Continued): The Marginal Effects of Election Fraud in Incumbent's Percentage on Postelectoral Transfers)



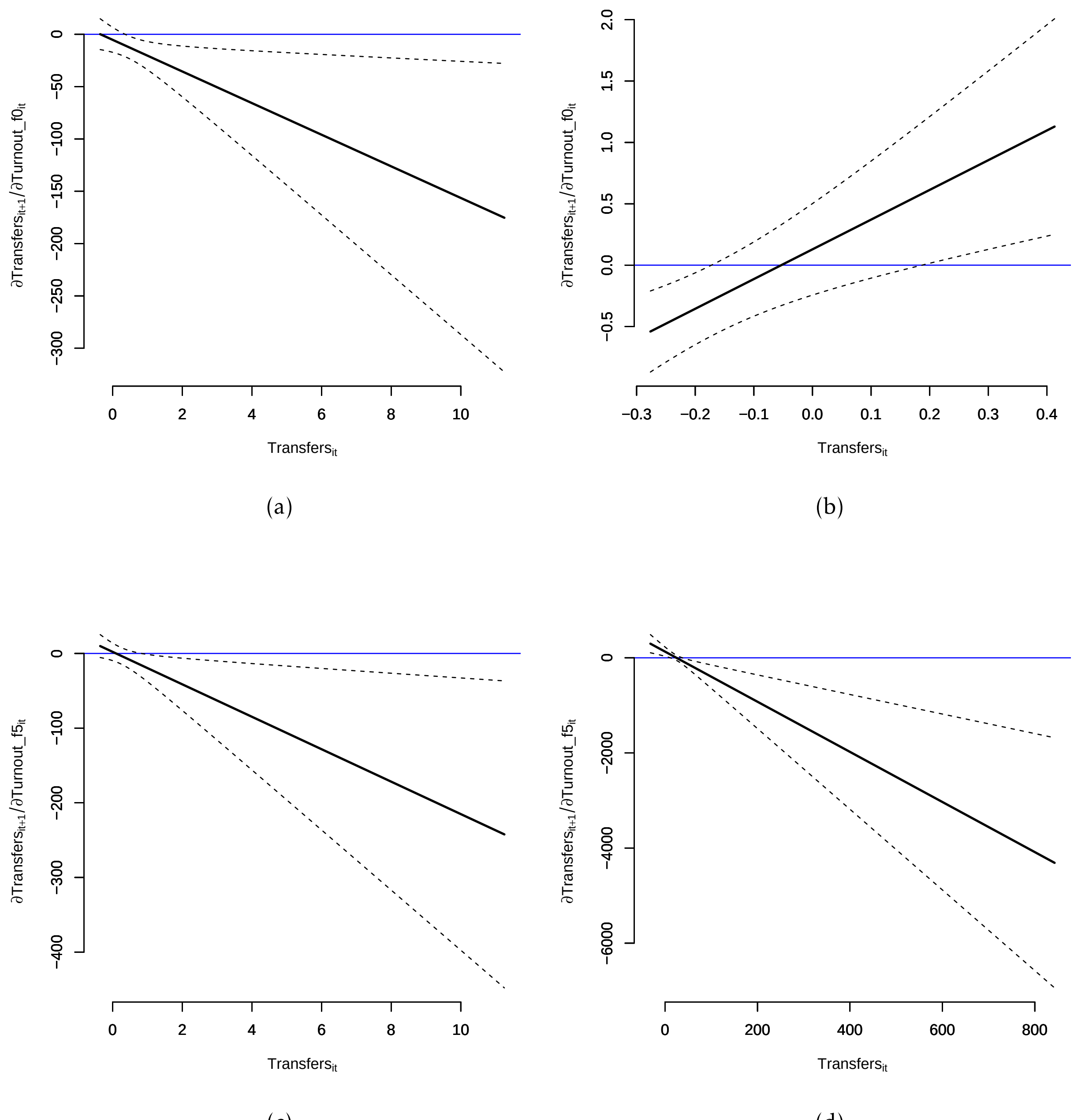
(e)



(f)

Notes: Estimated marginal effects for the models in Table 3.4: (a)M(01), (b)M(05), (c)M(03), (d)M(05), (e)M(02), (f)M(06). Figures show the marginal effect of election fraud on post-electoral transfers conditional on pre-electoral transfers.

Figure C.2: The Marginal Effects of Election Fraud in Turnout on Postelectoral Transfers)



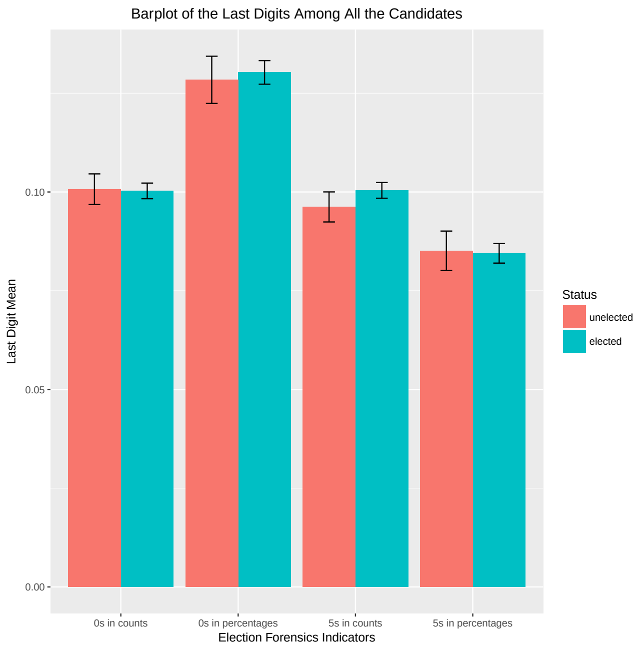
(a) (b) (c) (d)

Notes: Estimated marginal effects for the models in Table 3.4: (a)M(01), (b)M(06), (c)M(03), (d)M(05). Figures show the marginal effect of election fraud measured by different indicators on the post-electoral transfers conditional on the pre-electoral transfers in Russia.

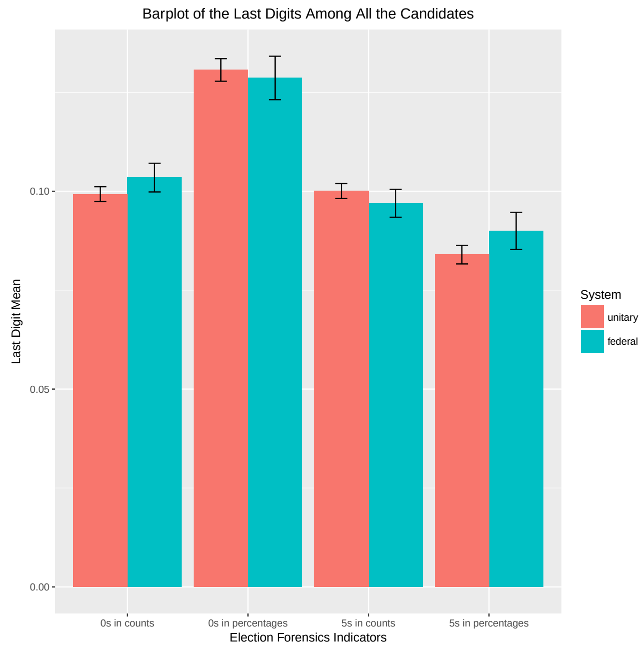
APPENDIX D

Supplementary Information for Chapter 2: Cross-National Analysis

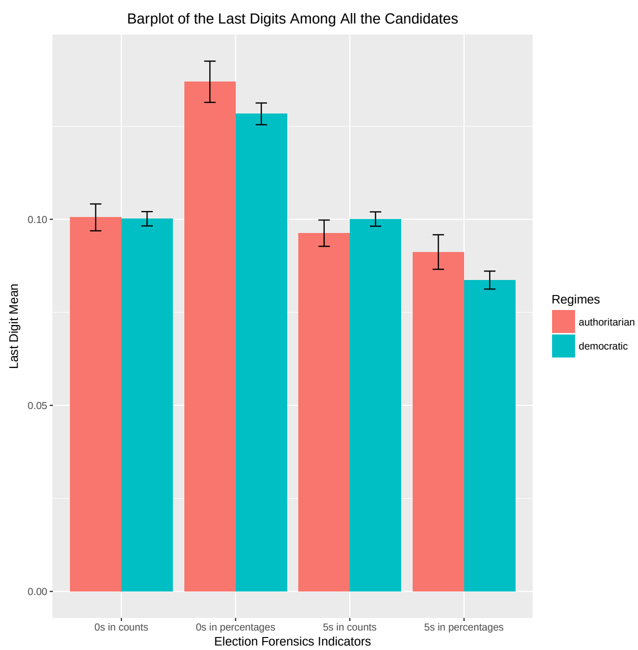
Figure D.1: Barplots for All Candidates



(a)



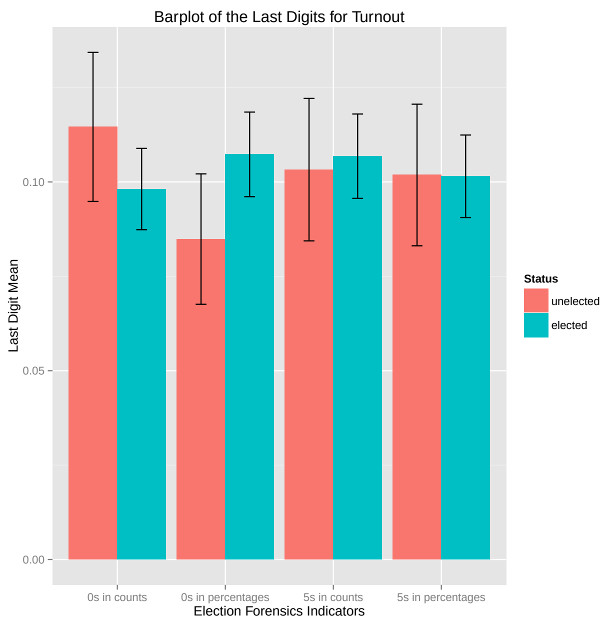
(b)



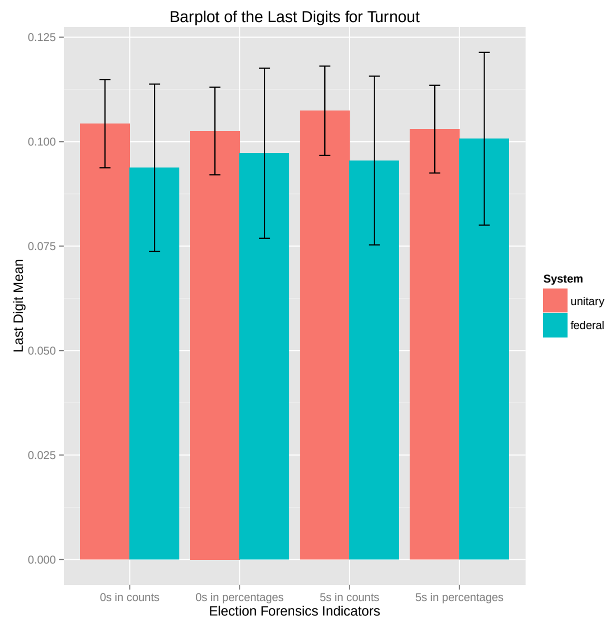
(c)

Notes: Barplots with 90% confidence intervals for all the candidates. Each barplot contains four groups of columns (from left to right): proportion of 0s in vote counts, proportion of 0s in vote percentages, proportion of 5s in vote counts, proportion of 5s in vote percentages.

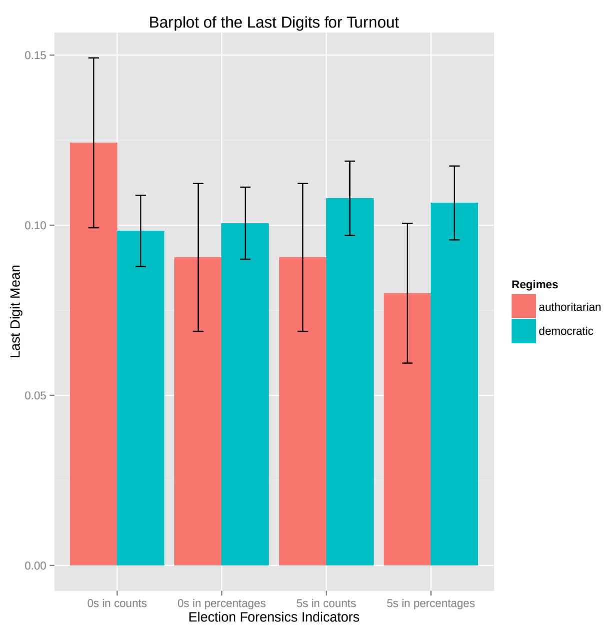
Figure D.2: Barplots for Turnout



(a)



(b)



(c)

Notes: Barplots with 90% confidence intervals for turnout. Each barplot contains four groups of columns (from left to right): proportion of 0s in vote counts, proportion of 0s in vote percentages, proportion of 5s in vote counts, proportion of 5s in vote percentages.

Table D.1: Summary of Results: Effect of $\hat{\lambda}$ on Financial Punishment

		$P05$	$T05$	F
Democracies	Federal	0.673	0.655	0.666
		(0.154)	(0.16)	(0.152)
	Unitary	0.802	0.816	0.793
		(0.149)	(0.083)	(0.148)
Autocracies	Federal	–	–	–
		–	–	–
	Unitary	0.994	0.997	0.993
		(0.004)	(0.001)	(0.004)

Notes: Standard errors in parentheses.

APPENDIX E

Supplementary Information for Chapter 3

Table E.1: Election Forecasts for the Incumbent by Polling Organizations

Pollsters/Incumbents	1996(1) Yeltsin	1996(2) Yeltsin	2000 Putin	2004 Putin	2008 Medvedev	2012 Putin
FOM	34.0	52.0	53.0	73.0	67.8	58.7
VCIOM	37.0	56.0	59.0	73.6	72.9	59.9
Levada-Center	—	—	—	73.7	79	66.0
Mean	*35.5*	*54*	*56*	*73.3*	*70.4*	*59.3*
Standard deviation	*2.1*	*2.8*	*4.2*	*0.4*	*5.6*	*3.9*
Official	**35.3**	**53.8**	**53.0**	**71.3**	**70.3**	**63.6**

Table E.2: Characteristics of the Surveys

	Sampling	Mode	RR	RR*	Weights
Levada-Center (Feb.17-20)	Quota	Face-to-Face	—	—	Postratification
Levada-Center (Feb.24-27)	Quota	Face-to-Face	—	—	Postratification
Levada-Center (March)	Quota	Face-to-Face	—	—	Postratification
Demoscope (March-April)	Multi-stage prob.	Face-to-Face	35.8	42.1	Postratification

Notes: Sampling frame wasn't not available for any of the surveys. RR – response rate, RR* – refusal rate.

Table E.3: Balance Test

Variables	(1)	(2)
Intercept	-0.041	0.052
	(0.217)	(0.216)
Sex	0.184⋆⋆	-0.012
	(0.072)	(0.072)
Age	-0.003	0.000
	(0.002)	(0.002)
Education	-0.02	0.018
	(0.036)	(0.036)
Wealth	0.045	0.072⋆
	(0.044)	(0.041)
Urban	-0.001	0.069
	(0.074)	(0.073)
Log-likelihood	-2205	-2273
Obs.	3191	4450

Notes: Significance levels: ⋆p ≤ 0.1, ⋆⋆p ≤ 0.05, ⋆⋆⋆p ≤ 0.01. *Models:* (1) – pre-electoral data; (2) – post-electoral data.

Table E.4: Distribution of Item Counts for the ICT, *in percentages*

		Putin's Support		Turnout	
	Item Counts	Control	Treatment	Control	Treatment
Pre-electoral	0	0.8	0.8	1.6	1.0
	1	43.2	29.1	40.4	19.5
	2	43.5	40.9	40.9	40.6
	3	11.4	22.6	15.1	26.8
	4	1.1	5.6	2.1	10.6
	5		1.0		1.4
Post-electoral	0	1.0	1.0	3.7	1.7
	1	39.5	26.5	36.7	17.1
	2	46.8	41.3	39.3	38.8
	3	11.1	23.5	18.5	31.1
	4	1.7	6.3	1.8	10.6
	5		1.5		0.7

Notes: Distribution of item counts across for the pre-electoral and post-electoral surveys.

Table E.5: Preference Falsification, Election Fraud and Margin of Victory in Russian Elections, 2012 (Linear Mixed-Effects Models)

	M(01)	M(02)	M(03)	M(04)	M(05)	M(06)
Constant	4.53***	−1.51***	−0.03***	4.49***	−1.51***	−0.02*
	(0.03)	(0.03)	(0.01)	(0.04)	(0.04)	(0.01)
Preference Falsification	-0.21	0.6***	0.16**	0.00	0.17	−0.1**
	(0.19)	(0.18)	(0.06)	(0.23)	(0.2)	(0.04)
Margin of Victory	-0.07	0.42***	0.23***	0.01	0.38***	0.2*
	(0.06)	(0.06)	(0.01)	(0.08)	(0.07)	(0.01)
Republics				-0.06	0.06	0.16***
				(0.05)	(0.05)	(0.02)
Rural				0.02	0.01	−0.03***
				(0.03)	(0.03)	(0.00)
Pref. Fals. X Margin of Victory	0.41	−1.42***	0.25***	0.00	−0.79**	0.23***
	(0.35)	(0.32)	(0.03)	(0.42)	(0.36)	(0.03)
Pref. Fals. X Republics				0.41	−0.63**	−0.34***
				(0.3)	(0.26)	(0.11)
Pref. Fals. X Rural				-0.17	0.52***	−0.05***
				(0.16)	(0.13)	(0.01)
Intercept	0.01	0.05	0.05	0.02	0.04	0.03
Residual	2.87		0.17	2.87		0.17
Log-Likelihood	161205	33621	21085	161209	33607	21297
Observations	65137	65137	65137	65137	65137	65137
Number of groups	40	40	40	40	40	40

Notes: Cluster robust standard errors in parentheses. Significance levels: *$p \leq 0.1$, **$p \leq 0.05$, ***$p \leq 0.01$. Dependent variables: M(01) – "VL", M(02) – "V05", M(03) – finite mixture estimator.

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